5-4-2016

Three Empirical Essays in the U.S. Beer Industry

Omer Hoke
University of Connecticut - Storrs, omer.hoke@uconn.edu

Three Empirical Essays in the U.S. Beer Industry

Omer Hoke, PhD

University of Connecticut, 2016

Abstract

The dissertation examines three empirical questions in the U.S. beer industry. The effect of large container consumption has been well explored in other food categories. However, its effect has been ignored in the U.S. beer industry. Although authorities have been imposing different public policies to lower negative externality of excessive alcohol consumption, statistics still clearly provide evidence related to severity of this problem. Therefore, first manuscript studies the impact of large container beer purchases on alcohol-related accidents. The study finds a statistically significant and positive relationship between large container beer purchases and alcohol-related accidents. Approximately 90% of the alcohol consumption by youth is in the form of binge drinking. Thus, second manuscript examines the impact of an unanticipated determinate of binge drinking behavior, minimum wage laws. The study finds a statistically significant and positive relationship between minimum wage increases and binge drinking among youth population. Third manuscript focuses on industry structure of the beer industry. There are many studies focusing on the impact of product variety on different outcome variables. Nonetheless, there is no study aiming to explore the impact of product depth on demand or supply side. In particular, the study examines the effect of product depth on market demand. Results suggest that an optimal product line depth for beer firms might be to provide more package size options than container size options.

Three Empirical Essays in the U.S. Beer Industry

Omer Hoke

B.A., Bilkent University, 2008

M.B.A., University of Hartford, 2010

M.A., University of Connecticut, 2012

M.S., University of Connecticut, 2014

A Dissertation

Submitted in Partial Fulfillment of the

Requirements of the Degree of

Doctor of Philosophy

at the

University of Connecticut

2016

APPROVAL PAGE

Doctor of Philosophy Dissertation

Three Empirical Essays in the U.S. Beer Industry

Presented by

Omer Hoke, B.A., M.B.A., M.A., M.S.

Major Advisor ____
Chad Cotti

Associate Advisor ____
Ben Campbell

Associate Advisor ____
Yizao Liu

\

University of Connecticut

2016

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my major advisor, Dr. Chad Cotti, for his priceless support in my dissertation. I appreciate all his time he spent with me with a great patience. His endless encouragement and support in my research were a great excitement for me during this journey. I consider myself very lucky to meet him and to learn empirical research from him. I also would like to thank my committee member, Dr. Ben Campbell, who was always supportive not only by providing opportunity for research projects but also by proving financial support. His financial support was priceless for me to survive during this journey. I also would like to take this opportunity to thank my other committee member, Dr. Yizao Liu, for her support in my dissertation. Furthermore, I would like to give a special thanks to Dr. Richard Dunn for his support during my study. He was always very helpful and caring. I improved my research skills enormously with his mentoring. Lastly, I would like to thank the Department of Agricultural and Resource Economics for financial support I received during my study.

A special thank goes to my mother, my wife, Anila Hoke, my sisters, and my brothers for their endless support for me during my PhD study. Their presence and support always helped me to smile and keep hard working during the hardest times of my life.

It is a great pleasure for me to dedicate this dissertation to my father, Sahin Hoke, and my mother, Sultan Hoke.

TABLE OF CONTENTS

Chapter 1: The Impact of Large Container Beer Purchases on Alcohol-Related Fatal Vehicle Accidents

Abstract

Using a fixed effect weighted least square model, we examine how changes in the share of beer purchases from large containers (>12oz) impact alcohol-related fatal accidents. We find that, after holding beer purchases and overall alcohol-consumption constant, an increase in total beer purchases from containers greater than the standard size of 12 oz. increases alcohol-related fatal accidents. We confirm our results persist across several investigations of robustness, as well as the use of instrument variables methods. Outcomes suggest that policy makers should consider differential excise taxes for the purchase of larger than standard size beer containers. Such a policy would likely reduce the number of alcohol-related fatal vehicle crashes and help to internalize the negative externalities associated with drunk driving. At the very minimum, these results suggest that individuals prone to dangerous levels of drunk driving are the consumers that most prefer large container size consumption. This is consistent with the idea that binge drinkers and beer drinkers are much more likely to drive while legally intoxicated.

1.1 Introduction

Excessive alcohol consumption has well-known adverse consequences, such as alcohol-related fatal accidents, diseases, injuries, crime, and violence. Given that many of the behaviors related to excessive alcohol consumption have negative externalities, curbing such behavior has meaningful social benefits. Consequently, there are various regulations imposed by the authorities to lower excessive alcohol consumption, such as excise taxes, Minimum Legal Drinking Age (MLDA) Laws, maximum Blood Alcohol Content (BAC) thresholds, hours of sale etc.

Of particular note, Levitt and Porter (2001) have shown that the negative externalities associated with drunk driving are quite high ($0.30 per mile driven while intoxicated). Statistics show that there were 9,878 fatalities in alcohol-related accidents, 31 percent of total traffic fatalities in 2011 in the U.S. (*National Highway Traffic Safety Administration, 2013*). Although authorities have been trying to mitigate this social problem by imposing various policies, there is still a need for further examination of the underlying determinates of drunk driving. Understanding what behaviors impact these negative outcomes and how individuals are best incentivized to prevent drunk driving is important to designing optimal public policy.

In this study we explore one unnoticed and potentially important factor affecting consumer behavior of alcohol; beer container sizes. In particular, we aim to examine the relationship between beer container size and alcohol-related fatal accidents. There are many studies discussing the impacts of policies aiming at reducing drunk driving. However, to our knowledge, this is the first study to investigate the relationship between beer container size purchases and the alcohol-related fatal accidents.

Unlike wine and liquor, which are typically consumed by the glass and have a greater shelf life after opened, beer is typically packaged and consumed in serving size containers (e.g. can or bottle). This difference is largely a function of the much shorter time period for which consumption of beer is optimal after opening. In recent years beer manufactures have begun to market beer in larger than standard (12 oz.) containers at a cheaper price per unit (ounce). The combination of the lower per unit price, larger container size, and a short consumption window after opening, may cause people to consume alcohol more quickly, or in greater quantities, or both. Hence, consumption of beer in larger container sizes may lead to greater average levels of intoxication and, subsequently, an increase in alcohol-related fatal vehicle accidents.

To investigate this issue we utilize data from two principle data sources, the Fatality Analysis Reporting System (FARS), which comprises detailed information about all fatal accidents in the U.S., and the Nielsen scanner panel data, which provides data on alcohol purchases from retail outlets. Empirically we employ a weighted least squares (WLS) fixed-effects model specification. Our results are consistent with the concern outlined above, as we observe an increase in alcohol-related fatal accidents in locations with increased sales of larger beer containers. In particular, we find that a 10% increase in beer purchases in containers greater than 12 oz. increases the number of alcohol-related fatal accidents by 1.95%. Additionally, a 10% increase in beer purchases in containers greater than 18 oz. increases the number of alcohol-related fatal accidents by 2.24%.

As we will demonstrate below, these estimates are robust to the inclusion of controls for area and time fixed effects, changes in population, and changes in factors that may influence overall driving risk separate from drinking behavior (e.g. construction, weather, etc.). Furthermore, these estimates are also robust to the estimation method selected (e.g., IV, weighted IV, ordinary least squares, negative binomial, etc).

Ultimately, this finding provides further insight into how uniform alcohol taxation may lead to sub-optimal outcomes. Specifically, it suggests that differential beer tax rates based on the size of the container might lead to improved social outcomes. According to the National Institute on Alcohol Abuse and Alcoholism, and several papers on the topic (e.g. Ruhm, 1996 ; Adams et al., 2012), beer taxes have a considerable impact on alcohol-related fatality rates, so policy makers should consider imposing different excises tax on beer purchases based on container size.

The paper proceeds as follows. Section 2 provides background of the regulations imposed to lower negative externality of excessive drinking, including a review of the literature on this issue. Section 3 explains our analysis of impact of large container beer purchases on alcohol-related fatal accidents in addition to explanations provided for the two data sources used. Results and implications are discussed in section 4. Section 5 concludes.

1.2 Background

According to the National Highway Traffic Safety Administration (NHTSA) an alcohol-related fatality occurred every 53 minutes in 2011 (a year with a very low number of accidents due to the recession). Moreover, Levitt and Porter (2001) show that drunk drivers impose an externality per mile driven of at least 30 cents because of their greater likelihood of causing fatal accidents. Additionally, total cost of alcohol-related accidents was estimated as $51.1 billion in 2000 (Blincoe L, et al., 2000).

The first notable attempt to reduce impaired driving in the U.S. was implemented in 1910 by the state of New York, which passed a formal impaired driving law (Fell and Voas, 2006). As automobile usage increased dramatically over the following decades, the costs associated with drunk-driving fatalities rose as well. In 1968 the National Highway Safety Bureau (now the NHTSA) reported formal and public concern relating to alcohol-impaired driving to Congress. Subsequently, over the last 40 years, governments at all levels have employed policy measures to curb drunk driving behavior, such as a range of alcohol taxes, age restrictions for consumption, blood alcohol limits while driving, sobriety check points, programs to educate the drivers, hours of sale, etc. Most of the existing research on the topic has focused on the impact of these regulations on the fatal accident rate.

As well explored in Tremblay and Tremblay (2005), firms in the beer industry differentiate their products along with objective, subjective, horizontal and vertical dimensions to protect themselves from direct price competition. Brewers not only apply vertical differentiation (e.g. freshness of a product) but also horizontal differentiation (e.g. light beer versus dark beer). Firms in beer industry, in addition to vertical and horizontal differentiation, also increase their product variety with different package and container sizes. The packaging varieties have been changing including different containers with different sizes, with much of change being in the form of larger than the standard 12oz container (Corey M. Reardon, 2004). This gives firms the ability to increase their profit and also discriminate price with different container and package sizes (cheaper per ounce prices) to extract more consumer surplus. However, this variation in package sizes alone may create larger negative consequences from the consumption of beer.

While previous studies on drunk driving have not focused on the consequences of beer container size, the impact of container size on consumption has been well explored in different food categories. For example, Wansink and Kim (2005) conducted an experiment which shows that people at a movie theater eat 45.3% more popcorn, when they are given popcorn in large containers. Additionally, in order to understand if this result is still valid regardless of the taste of popcorn, they provide the respondents with popcorn which is stale and of lower quality. Nevertheless, people still consume 33.6% more popcorn than the amount they did of fresh popcorn in standard size containers. Collectively these results indicate that large containers lead to overeating. Moreover, experiments done by Marchiori et al. (2012) on snack consumption also show that larger container size increases the food intake, in this case by 129%. Consistent with these findings, researchers and health organizations recommend using smaller containers in order to improve health outcomes.[1] These findings and recommendations would suggest that increased beer container size may lead to increased consumption, all else equal.

Studies that have focused specifically on alcohol demonstrate that many consumers prefer larger container sizes. According to an experiment conducted by Kaskutas and Graves (2000), individuals were shown the alcohol drinks with different sizes, and 48% of the respondent's preferred container size was greater than 12 oz. standard size. Moreover, larger container sizes may lead to increased pace of consumption, perhaps as consumers attempt to finish their beer before it gets warm or flat. If common, such behavior would increase average blood alcohol content levels. The result of increased consumption pace is sensible if one considers the Windmark formula used by National Traffic Safety Administration to estimate BAC;

$$EBAC = (0.806 * SD)/(BW * W_t) – (MR * DP)$$

SD is the number of standard drinks; BW is the body water constant; W_t is the body weight and MR is the metabolism rate. DP is the drinking period, number of hours an individual drink a certain amount of alcohol. Clearly, an increase in DP would give a lower BAC threshold whereas

[1] National Institutes of Health, National Heart, Lung, and Blood Institute (1999); Department of Agriculture, Center for Nutrition Policy and Promotion (2002).

a lower DP, shorter period of time, would result in the opposite. Additionally, given the average human liver can only process approximately one drink in an hour,[2] faster consumption or larger amounts of consumption (both possible outcomes of larger container size) will cause increased levels of inebriation.[3]

In the remainder of the paper, we investigate whether these related outcomes translate to increased fatal vehicle accidents by observing alcohol purchase behavior. We find substantial evidence that the number of fatal accidents involving alcohol increases as the share of beer purchases of larger than standard containers increases.

1.3 Data and Methods

A. Data Sources

To examine how changes in the share of beer purchases from large containers impacts alcohol-related fatal accidents we utilize two primary data sources. First, the Nielsen Scanner Database (NSD) obtained from the Zwick Center for Food and Resource Policy (the Food Marketing Policy Center) at the University of Connecticut, which provides detailed information on beer purchases, brands, container sizes, etc. of purchases in a series of locations across the US, and is designed to provide a representative sample of purchase habits for different locations across the U.S. Specifically, the NSD data are aggregated by Nielsen Designated Market Areas (DMA), which are the geographic areas defined by Nielsen Media Research Company as a group of counties that make up a particular retail marketplace. The frequency of observation is rolling four week blocks (which we will often refer to as "monthly" for simplicity) from 2008 and 2011, and covers the

[2] Prevention Resource Guide: Impaired Driving (1991) MS434 Safer Streets Ahead (1990) PH292.
[3] National Institute on Alcohol Abuse and Alcoholism.

following twelve marketplaces: Atlanta, Boston, Chicago, Dallas, Detroit, Hartford, Los Angeles, Miami, New York, San Francisco, Seattle and Syracuse.

Of primary interest is the monthly amount of both total beer purchases in ounces in a DMA and total beer purchases in a DMA from large containers. Given that 12 fluid ounces is the standard size container for beer, we define containers (bottle or can) greater than 12 ounces as large, although we will also define containers of greater than 18 fluid ounces as large in certain specifications to demonstrate consistency in our findings.[4]

Table A1 (in the Appendix) displays the distribution of sizes of individual containers present in the data, by package, brand, and/or container type. Thus, for instance, Table A1 shows that there are 395 versions of beer products (e.g. Budweiser six-pack cans, Budweiser twelve pack bottles, Miller six-pack cans, etc.) where the base container size (e.g. can, bottle) was seven ounces. About 27% of the variety in package, brand, size, and container type combinations includes beer products of greater than 12 ounces. As we capture monthly quantities sold for each type of beer products from Nielsen Scanner Data by each DMAs, we aggregate the quantities to find total beer purchases in ounces and our variables of interest.

We link NSD data on DMA-level beer purchases with fatal vehicle crash data obtained from the Fatality Analysis Reporting System (FARS) maintained by the National Highway Traffic Safety Administration (NHTSA). The FARS provides a near census of fatal automobile accidents in the US, and is designed to track patterns in accident rates across the country. It provides detailed information about the driver and the accident, which will allow us to identify the time and location of all accidents, as well as the blood alcohol content of the drivers, so that alcohol-related accident

[4] Total beer purchases of containers greater than 12 ounces and 18 ounces are highly correlated with total beer purchases (r=0.90), as one would anticipate.

counts can be identified separately.[5] Hence, the dependent variable in our analysis will be the number of fatal accidents in a DMA-time period in which at least one driver has a blood alcohol concentration (BAC) greater than 0.[6] We will also utilize the number of non-alcohol-related accidents (BAC=0) in an area as an important control, which we discuss below.

In addition to data from the NSD and the FARS, we also include data from other sources in our models. These include data total alcohol consumption from beer, wine and spirits collectively, which was obtained from National Institute on Alcohol Abuse and Alcoholism,[7] and annual population of each DMA, available by aggregating county population data from the US Census Bureau. Table 1 reports descriptive statistics for our variables form as used in the estimation process.[8]

B. Empirical Methodology

Our basic empirical strategy is given by the following specification:

$$Ln(Accidents_{itw}) = \beta_0 + \beta_1 Ln(Container12_{itw}) + \beta_2 Ln(Nobac_{itw}) + \beta_3 Ln(BeerPurchases_{tw}) + \beta_4 Ln(Population_{it}) + \beta_5 Ln(AlcoholConsumption_{itw}) + \beta_6 T_{tw} + \beta_7 L_i + \beta_8 T_{tw} L_i + \mathcal{E}_{itw} \quad (1)$$

where subscript i denotes the DMA, t denotes year and w denotes a particular four-week period of a year (e.g. first, second, etc.). The terms T_{tw} and L_i are time and the DMA fixed effects. The inclusion of fixed effects is vital in this context and helps alleviate one major concern of this analysis—specifically, capturing differences in accidents across DMA that are time-invariant and

[5] Although required by law, BAC levels are not collected for every crash, hence the standard practice of using the NHTSA imputed BAC for missing observations that is provided in the FARS dataset is employed here (Klein, 1986; NHTSA, 2002; Rubin et al., 1998).
[6] Aggregation is designed to match the four week rolling blocks that are provided in the NSD.
[7] http://pubs.niaaa.nih.gov/publications/surveillance97/tab3-1_11.htm.
[8] Appendix Table A2 provides break outs of the annual variation in total beer purchases from large container (>12oz) for each DMA in the sample.

differences in accidents across time that are common in all DMAs. $T_{tw} L_i$ denotes controls for time varying effects by DMA, which will account for potential differences in uncaptured trends across locations.

Our dependent variable, $Ln(Accidents_{itw})$, is the log of total number alcohol-related fatal accidents in which the driver has a BAC level greater than 0 in a given DMA-year-month cell. We judge logs to be the most appropriate measure of the dependent variable because the median estimated number of fatal accidents for a DMA-month in the sample is less than the mean.[9] We show later that redefining the dependent variable or using a different estimation model yields qualitatively identical results.[10]

Our principle variable of interest is the log of $Container12_{itw}$, total beer purchases of containers greater than 12 ounces. Twelve ounce containers are considered standard in the industry as they are overwhelmingly the most common container size purchased in the market. This is also the clinically accepted measure for "one drink" when consuming beer. So, β_1 represents the percentage change in alcohol-related accidents with respect to ounces of beer purchased from large container size. Note, we are also controlling for total beer purchases ($BeerPurchases_{itw}$) and overall alcohol consumption ($AlcoholConsumption_{itw}$) from all alcohol types and sources (not just retail purchases). These measures will account for changes in *overall alcohol consumption* habits in a DMA, and will also capture the impact of related public policies that may impact alcohol purchases habits (both in retail stores or at bars and restaurants) and might change during the time period

[9] Given that the number of accidents may be highly variable in smaller DMAs, in certain specifications we will weigh the OLS estimates by DMA-time period population. We also correct all standard errors to allow for non-independence of observations from the same DMA through clustering. This follows the work of Arellano (1987) and Bertrand et al. (2004). That said, given that we have a smaller number of clusters we also use the bootstrap approach outlines by Cameron et al. (2008) and verify that our results are still robust.

[10] For example, Poisson, Negative Binomial, etc.

under investigation, such as beer taxes or dram shop laws. Hence, changes in *Container12* reflect effects from changes in the distribution of alcohol purchases between small/standard (<=12 oz) and large container size (>12 oz).

We understand that our empirical strategy must isolate the impact of changes in the share of large container size purchases aside from the other determinants of alcohol-related accidents. Our empirical approach addresses this in a number of ways. Specifically, we recognize that, while the DMA fixed effects capture differences in DMA that might affect accidents and are constant over time, we also should add various covariates that capture DMA-specific changes in a DMA's alcohol-related crashes over time. The first control we include is the log of the DMA's population obtained from the US Census Bureau, as population growth will likely increase accidents. The non-alcohol-related fatal crashes are included to summarize time-varying attributes that influence overall crash risk across locations, e.g., gas prices, miles driven, general economic activity, highway construction, and weather patterns. This is an important independent variable, as it parsimoniously controls for both observed and unobserved characteristics that influence crash risk, and thus is expected to be positively related to fluctuations in the alcohol-impaired fatal crash rate (Adams & Cotti, 2008).

The identification strategy explained to this point is predicated on the assumption that after controlling for fixed effects and time varying controls, total beer purchases and total alcohol consumption, we can estimate the impact of changes in the share of large container beer purchases on alcohol-related accidents. However, we have treated our variable of interest, *Container12*, as exogenous in our study. Given that purchase selection exists, this assumption might not be correct; consumer choice in container size may be correlated with other factors which are not observable by the researcher. We attempt to account for the presence of this possible endogeneity problem by also estimating an Instrumental Variables (IV) model. Specifically, we use lags of the variable of interest as an instrument. Results (provided below) are robust. Moreover, the Hausman test fails to reject the null hypothesis that DMA-level beer purchases from large container cans and bottles are exogenous.

1.4 Empirical Results

A. Basic Outcomes

We are interested in identifying if an increase in the distribution of beer purchases toward larger container purchases results in a rise in alcohol-related fatal accidents. Column (1) of Table 2 displays the outcomes from our basic WLS estimation of equation (1). Estimates are positive and highly statistically significant (P-Value=0.001), suggesting that, after holding total beer purchases and overall alcohol consumption constant, a 10% increase in total beer purchases of containers greater than 12 ounces rises alcohol-related fatal accidents by 1.95%.[11] Given the average number of accidents by DMAs in our sample in 183.17 per year, this translates to an overall increase approximately 3.6 more alcohol-related fatal accidents in a year for the average DMA.[12]

For robustness, in column (2) the variable of interest is redefined as *Container18* (50% greater than standard size), where large container is defined as greater than 18 fluid ounces of beer. Results

[11] Results are robust to Poisson (*Container12*: Coefficient = 0.231, P-Value = 0.000, Standard Error = 0.059) and Negative Binomial (*Container12:* Coefficient = 0.231, P-Value = 0.000, Standard Error = 0.059).
[12] To the extent that there is measurement error in the data, that estimates presented in Table 2 may suffer from attenuation bias and be biased toward zero.

are consistent (P-Value=0.002) and a bit larger, as one would anticipate if container size plays a meaningful role in drunk driving outcomes.[13]

Next, in the final two columns of Table 2, weighting is dropped, yielding similar outcomes. Taken at face value, these results such strongly that, all else equal, larger container size options lead to increased alcohol-related accidents, and possibly due to greater levels of intoxication caused by increased pace or amount of alcohol-consumption.

The estimates for other independent variables tend to be as expected, with *NoBAC* (which captures general accident risk), *Total Beer Purchase,* and *Total Alcohol Consumption* all having a positive impact on alcohol-related fatal accidents. The one exception would be *Population,* which provides a very imprecisely measured negative coefficient. This is likely because most of the changes effected by population size of the states are captured through the aggregate beer purchase and alcohol consumption variables.

Lastly we want to verify that our baseline results aren't driven by outliers. Specifically, while the vast majority of purchases captured by *Container12* comes from purchases from 13oz to 40oz in container size, there is a small component of off-premises (packaged) consumption that comes from greater than 500 oz containers (i.e. half barrels, etc.). As discussed in the introduction and background, a potential mechanism for how shifts in container sizes impact accident outcomes maybe driven by changes in patterns surrounding the consumption of individual-sized containers (e.g. cans/bottles). Hence, we want to verify that our results are not driven by variation in outliers, such as half-barrels, and robust to restriction to purchases of container sizes that at commonly for

[13] Results are robust to Poisson (*Container18:* Coefficient = 0.24, P-Value = 0.000, Standard Error = 0.038) and Negative Binomial (*Container18:* Coefficient = 0.24, P-Value = 0.000, Standard Error = 0.038). Results are also robust to other cutoff levels (i.e. 13oz, 14oz, etc.) that are sensible for containers intended for individual consumption.

individual purposes. To facilitate this investigation we re-estimate our baseline model for two different definitions of "large container" purchases. First, we restrict our large container definition to containers between 12 and 41 ounces, which reflect purchases of containers larger than standard size (12 ounces) but still intended for individual consumption. Second, we alternatively restrict our large container definition to purchases greater than 40 ounces, which reflects purchases of containers that are typically not intended for individual consumption. Estimates of the impact of increases in purchases of beer in containers between 12 and 41 ounce on alcohol-related fatal accidents is basically the same as presented in Table 2 (Coef. = 0.204; P-value< 0.001). Conversely, purchases greater than 40 ounces yield no significant effect (Coef. = 0.013; P-value = 0.177). Collectively this strongly suggests the baseline results are, indeed, driven by changes in beer purchases from larger *individual-sized* beer containers.

Instrumental Variables Estimation

An additional concern that one may have is that the results found in Table 2 might be hampered by endogeneity. Specifically, *Container12* (total beer purchases of containers greater than 12 oz.) and *Container18* (total beer purchases of containers greater than 18 oz.), might be potentially correlated with unobservable time-varying factors that impact or outcome of interest. To test the endogeneity problem directly, we conduct Durbin-Wu-Hausman endogeneity test for both variables, *Container12* and *Container18*. The test fails to reject the null hypothesis of variables are exogenous (P-Value=0.72 for *Container12* and 0.71 for *Container18*). This suggests that variables can be treated as exogenous and, coupled with the nature of the empirical specification presented in equation (1), that omitted variable bias is not likely to confound the initial estimates meaningfully.

However, with the goal of being comprehensive, we undertake a formal instrumental variables analysis. This method requires that we identify an instrument which is correlated with the endogenous variable but not with the error term in the model. Importantly, given that we are using a fixed effects framework, we need to find an instrument variable which also varies over time. As if often the case, strong IV candidates are not available. The instrument we use is the value of *Container12* lagged one period. The lagged variable is correlated with *Container12*, but should not be correlated with the number of alcohol-related accidents in the period in question. Specifically, changes in lagged measures of *Container12* are unlikely to impact future period accident outcomes, as the impact of alcohol consumption on drunk driving is immediate in this context. That said, using lagged variables as instruments can be problematic and the results should be interpreted with caution, accordingly. Below we also provide information on the explicit set of tests deigned to verify the validity of this instrument.

We utilize a two stage least squares approach where we estimate first stage by the following model:

$$Ln(Container12_{itw}) = \beta_0 + \beta_1(Ln(Container12_{it-1w})) + \beta_2 Ln(Nobac_{itw}) + \beta_3 Ln(BeerPurchases_{tw}) + \beta_4 Ln(Population_{it}) + \beta_5 Ln(AlcoholConsumption_{itw}) + \beta_6 T_{tw} + \beta_7 L_i + \beta_8 T_{tw} L_i + \mathcal{E}_{itw} \qquad (2)$$

where subscript i denotes the DMA, t denotes year and w denotes four-week periods. The terms T_{tw} and L_i are time and the DMA fixed effects. $T_{tw} L_i$ denotes controls for time varying effects by DMA. Our principle variable of interest, the log of $Container12_{itw}$ is dependent variable in first stage regression. Total beer purchases ($BeerPurchases_{itw}$) and overall alcohol consumption ($AlcoholConsumption_{itw}$) are also included in the first stage regression. $Nobac_{itw}$ denotes non-alcohol-related fatal crashes and $\mathcal{E}_{itw}$ is the residual. We will also follow the same approach for our other variable of interest, *Container18.*

The results of the first stage regression are given in Table A3 in the appendix. As the results show, the coefficients of the lag instrumental variable for both endogenous variables, *Container12* and *Container18*, are statistically significant at 1% level (P-Value=0.000). Importantly, results depict that an increase in lag value of our instrument would result in an increase in total beer purchases of larger containers.

We also conduct an F-test to test the strength of the instrument. F-statistics show that we can reject the null hypothesis of weak instrument. In particular, the F-statistic for our endogenous variable, *Container12*, is 161.87 which is considerably greater than rule of thumb of ten. Additionally, we calculate the Stock and Yogo test which depicts the critical values for 2sls estimation. Since F-statistic, 161.87 is greater than 5% critical value of Wald test, 16.38, we reject the null hypothesis of weak instruments. F-statistic for our second endogenous variable, *Container18*, is 310.06. As this value exceeds both rule of thumb of 10 and 5% Wald test critical value, we again reject the null hypothesis of weak instrument.

Table 3 depicts the second stage results. The first two columns of Table 3 provide the estimates of weighted IV approach, and the last two provide the same estimates, but unweighted. Outcomes from the IV approach are very similar to the WLS/OLS outcomes reported in Table 2, and in all cases support our earlier findings, as the variables of interest (*Container12* and *Container18*) are still positive and statistically significant.

As seen in column 1 of Table 3, coefficient of *Container12* is 0.164 (P-Value=0.013) suggesting that a 10% increase in total beer purchases of containers greater than 12 ounces rises fatal crashes by 1.64%, compared to 1.95% in the WLS model. Similarly, a 10% rise in *Container18*, total beer purchases of containers greater than 18 ounces brings 2.15% (P-Value=0.061) increase in alcohol-related accidents compared to 2.24% in our basic specification. Furthermore, the third and fourth columns of Table 3 depict estimates of the unweighted IV model and are identical to our main results. Coefficient for *Container12* and *Container18* are still statistically significant (P-Value=0.001 and 0.03 respectively).

1.5 Conclusion

Heavy alcohol consumption is a severe problem not only for the authorities but also for society. It has both social and economic implications, including diseases, injuries, crime, violence, etc. In this study we focus on one of the important consequences of heavy drinking; alcohol-related fatal vehicle accidents. There were 9,878 fatalities in alcohol-related accidents in 2011. Estimated total cost of alcohol-related accidents was $51.1 billion in 2000 (Blincoe L, et al., 2000*).* Thus, this problem has not only social importance for the policy makers but also economic and behavioral implications which need to be fully understood.

Unlike wine and liquor, which are typically consumed by the glass and have a greater shelf life after opened, beer is typically packaged and consumed in serving size containers (e.g. can, bottle, etc.). This difference is largely a function of the much shorter time period for which consumption of beer is optimal after opening. The combination of the lower per unit price associated with larger container size and short consumption window after opening may cause people to consume alcohol more quickly, or in greater quantities, or both. Hence, consumption of beer in larger container sizes may lead to greater average levels of intoxication and, subsequently, an increase in alcohol-related fatal vehicle accidents. Even though the impact of container size on consumption has been well explored in different food categories, its impact on beer consumption or drunk driving accidents has not been studied in detail.

Our findings show that, after accounting for total beer purchases and overall alcohol consumption, an increase in beer purchases from larger than standard size containers is significantly associated with an increase in alcohol-related fatal accidents. Such an outcome suggests that policy makers should consider a beer tax based on the size of the containers, as it should lower the alcohol-related fatal crashes rate and help to internalize the negative externalities associated with drunk driving. At the very minimum, these results suggest that individuals prone to dangerous levels of drunk driving are the same people who most prefer large container size consumption. This is consistent with the idea that binge drinkers and beer drinkers are much more likely to drive while legally intoxicated (Cotti et al. 2014). A limitation of our results is that Nielsen scanner panel data do not include purchases from restaurant and bars, thus are only explicitly relatable to off-premises purchases. However, to the extent that purchase habits at a point and time are correlated between on-premises and off-premises location, inference should be consistent.

References

Adams, Scott, and Chad, D. Cotti, "Drunk Driving after the Passage of Smoking Bans in Bars," *Journal of Public Economics* 92:5-6 (2008), 1288-1305.

Adams, Scott, McKinley, L. Blackburn, and Chad, D. Cotti, "Minimum Wages and Alcohol-Related Traffic Fatalities among Teens", *Review of Economics and Statistics* (2012), 94(3): 828-840.

Arellano, M., "Computing Robust Standard Errors for Within-Group Estimators", *Oxford Bulleting of Economics and Statistics,* 49, 4 (1987), 0305-9049.

Bertrand, M., Duflo, E. and Mullainathan, S., "How Much Should We Trust Difference in Differences Estimates?", *The Quarterly Journal of Economics* (2004), 119 (1): 249-275.

Blincoe, L. J., Seay, A. G., Zaloshnja, E., Miller, T. R., Romano, E. O., Luchter, S., and Spicer, R. S., "The Economic Impact of Motor Vehicle Crashes 2000", *Washington DC: U.S. Department of Transportation, National Highway Traffic Safety Administration* (2002).

Cameron, A. C., Gelbach, J. G., and Miller, D. L. (2008), "Bootstrap-Based Improvements for Inference With Clustered Errors," *Review of Economics and Statistics*, 90, 414–427.

Chad, D. Cotti, Richard, A. Dunn, and Tefft, Nathan (2014), "Alcohol-Impaired Motor Vehicle Crash Risk and the Location of Alcohol Purchase", *Social Science & Medicine*, forthcoming.

Corey M. Reardon (2004), "A New Definition," Label Feature Report, Primedia Business Magazines & Media, Inc.

Eisenberg, D., "Evaluating the Effectiveness of Policies Related to Drunk Driving", *Journal of Policy Analysis and Management* 22 (2) (2003), 249–274.

Fell, C.J. and Voas, R.B, "Mothers Against Drunk Driving (MADD): the First 25 Years", *Traffic Injury Prevention* 7:3 (2006), 195–212.

Kaskutas, A. L. and Graves, K., "An Alternative to Standard Drinks as a Measure of Alcohol Consumption", *Journal of Substance Abuse* 12 (2000), 1-2, 67-68.

Klein, T.M. (1986), "*A Method for Estimating Posterior BAC Distributions for Persons Involved in Fatal Traffic Accidents"* DOT HS 807094, National Highway Traffic Safety Administration, Department of Transportation.

Levitt, D. S. and Porter, J., "How Dangerous Are Drinking Drivers?", *Journal of Political Economy*, (2001), vol. 109, no. 6.

Marchiori, D, Corneille, O. and Klein, O., “Container Size Influences Snack Food Intake Independently of Portion Size”, *Appetite* 58 (2012), 814-817.

National Institute on Alcohol Abuse and Alcoholism, Source: http://pubs.niaaa.nih.gov/publications/aa35.htm.

National Institutes of Health, National Heart, Lung, and Blood Institute (1999), “*Clinical guidelines on the identification, evaluation, and treatment of overweight and obesity in adults – highlights for patients*”, Bethesda, MD: U.S. Department of Health and Human Services Publication #55–909.

Prevention Resource Guide: Impaired Driving (1991) MS434 Safer Streets Ahead (1990), PH292, Source: http://chavesdwiprogram.us/pdf/Effects%20of%20Alcohol%20Intoxication.pdf.

Rubin, D.B., Shafer, J.L., and Subramanian, R. (1998) “*Multiple Imputation of Missing Blood Alcohol Concentration (BAC) Values in FARS”,* DOT HS 808816, National Highway Traffic Safety Administration, and Department of Transportation.

Ruhm, Christopher J., ‘‘Alcohol Policies and Highway Vehicle Fatalities,’’ *Journal of Health Economics* 15(4) (1996), 435–454.

Tremblay J. V. and Tremblay H. C. (2005), “The U.S. Brewing Industry: Data and Economic Analysis,” Cambridge, MA: MIT Press.

U.S. Department of Agriculture, Center for Nutrition Policy and Promotion (2002), “*How much are you eating? Putting the Guidelines into Practice*”, Home and Garden, Bulletin No. 267–1.

Wansink, B. and Kim, J., “Bad Popcorn in Big Buckets: Portion Size Can Influence Intake as Much as Taste”, *Journal of Nutrition Education and Behavior* (2005), 37:242-245.

TABLE 1. – DMA LEVEL DESCRIPTIVE STATISTICS

	Obs	Mean	Std. Dev.	Min	Max
Accidents (BAC>0)	624	14.09	8.11	0	50
Accidents (BAC==0)	624	26.40	16.58	3	102
Total Packaged Beer Purchases (in million ounces)	624	109	87.4	11.5	461
Population (in million)	624	8.1	5	1.9	20.3
Total Alcohol Purchases- any source (in million ounces)	624	999	604	221	2,390
Total Packaged Beer Purchases (>12 oz.)	624	12.6	12.2	0.243	60.1
Total Packaged Beer Purchases (>18 oz.)	624	7.9	11.8	0.183	56.9

Table 2. WLS and OLS ESTIMATES FOR THE DETERMINANTS OF FATAL ALCOHOL-RELATED ACCIDENTS

	(1)		(2)	
	WLS with Transformed Dependent and Independent Variables		**OLS with Transformed Dependent and Independent Variables**	
	(1)	(2)	(3)	(4)
Container12	0.195***	-	0.225***	-
	(0.0444)	-	(0.069)	-
Container18	-	0.224***	-	0.236***
	-	(0.0539)	-	(0.059)
Non-Alcohol-Related Accidents	0.241***	0.243***	0.209***	0.212***
	(0.0561)	(0.0554)	(0.062)	(0.061)
Beer Consumption	0.269	0.241	0.161	0.140
	(0.163)	(0.163)	(0.269)	(0.254)
Population	-5.099	-4.768	-1.117	-0.853
	(4.062)	(3.669)	(5.480)	(5.087)
Alcohol Consumption	5.017	4.806	3.982	3.837
	(3.302)	(3.035)	(3.484)	(3.246)
Sample Size	624	624	624	624

All regressions include both DMA and year fixed effects. The sample size is 624 observations come from 12 DMAs (Designated Market Areas), 4 years and 13 four months period in a year. Column 1 is estimated by weighted least squares using the log of total number alcohol-related fatal accidents in which the driver has a BAC level greater than 0 in a given DMA-year-month cell as a dependent variable. Column 2 is also estimated by weighted least squares with a different variable of interest, , the total beer purchases of containers greater than 18 ounces. For both column 1 and 2, weights are formed as population of a given DMA and time. Column 3 and 4 are estimated by ordinary least squares. The only difference between column 3 and 4 is the variable of interest used. While column 3 uses the total beer purchases of containers greater than 12 ounces, as a variable of interest, column 4 uses *the total beer purchases of containers greater than 18 ounces*. Standard errors are in parentheses and are clustered at the DMA level to allow for arbitrary patterns in heteroskedasticity and correlation in errors over time in a given DMA. *** denotes statistical significance at 1% level.

Table 3. IV ESTIMATES FOR THE DETERMINANTS OF FATAL ALCOHOL-RELATED ACCIDENTS

	(1)		(2)	
	Weighted IV		**IV**	
	(1)	(2)	(3)	(4)
Container12	0.164**	-	0.207***	-
	(0.066)	-	(0.064)	-
Container18	-	0.215*	-	0.273**
	-	(0.115)	-	(0.126)
Non-Alcohol-Related Accidents	0.238***	0.239***	0.205***	0.209***
	(0.050)	(0.049)	(0.055)	(0.055)
Beer Consumption	0.306**	0.264	0.186	0.122
	(0.147)	(0.167)	(0.245)	(0.266)
Population	-5.936*	-5.505*	-1.956	-1.350
	(3.606)	(3.234)	(4.849)	(4.459)
Alcohol Consumption	5.495*	5.264*	4.41	4.149
	(2.953)	(2.694)	(3.119)	(2.849)
Sample Size	612	612	612	612

All regressions include both DMA and year fixed effects. The sample size is 612 observations come from 12 DMAs, 4 years and 13 four months period in a year. Column 1 is estimated by weighted least squares with instrument variable using the log of total number alcohol-related fatal accidents in which the driver has a BAC level greater than 0 in a given DMA-year-month cell as a dependent variable. Instrument variable used is lag of the endogenous variable, total *beer purchases of containers > 12 ounces*. Column 2 is also estimated by weighted least squares with instrument variable. The variable of interest is different than the one in column 1; total beer purchases of containers greater than 18 ounces. Instrument variable is lag of the endogenous variable, total *beer purchases of containers > 12 ounces*. For both column 1 and 2, weights are formed as population of a given DMA and time. Column 3 and 4 are estimated by instrument variable technique. The only difference between column 3 and 4 is the variable of interest used. While column 3 uses *Container12*, total beer purchases of containers greater than 12 ounces, as a variable of interest, column 4 uses *Contianer18*. Instrument variables are the lags of the variables of interest. Standard errors are in parentheses and are clustered at the DMA level to allow for arbitrary patterns in heteroskedasticity and correlation in errors over time in a given DMA. ***, **,* denote statistical significance at 1%, 5% and 10% level respectively.

Appendix

Table A1: Distribution of products in the data set in terms of ounces

oz	Freq.	Percent	Cum.
7	395	1.36	1.36
8	61	0.21	1.57
8.5	2	0.01	1.58
9	16	0.06	1.63
9.4	1	0	1.63
10	22	0.08	1.71
10.1	1	0	1.71
11	52	0.18	1.89
11.15	131	0.45	2.34
11.16	8	0.03	2.37
11.2	1,785	6.14	8.51
11.5	266	0.92	9.43
11.6	2	0.01	9.43
12	18,529	63.74	73.18
12.5	13	0.04	73.22
12.68	9	0.03	73.25
12.7	57	0.2	73.45
13	11	0.04	73.49
14.9	50	0.17	73.66
15.2	4	0.01	73.67
16	1,585	5.45	79.12
16.1	20	0.07	79.19
16.9	1,161	3.99	83.19
17	166	0.57	83.76
18	10	0.03	83.79
18.7	73	0.25	84.04
19.25	5	0.02	84.06
20.3	19	0.07	84.13
21	3	0.01	84.14
21.4	49	0.17	84.31
21.6	56	0.19	84.5
22	812	2.79	87.29
22.3	13	0.04	87.34
22.31	1	0	87.34
22.4	48	0.17	87.51
23.6	5	0.02	87.52
24	1,617	5.56	93.09
25	48	0.17	93.25

25.3	22	0.08	93.33
25.35	28	0.1	93.42
25.4	614	2.11	95.53
26	14	0.05	95.58
30.4	7	0.02	95.61
32	384	1.32	96.93
33.8	30	0.1	97.03
33.82	2	0.01	97.04
40	320	1.1	98.14
46.5	12	0.04	98.18
50.7	15	0.05	98.23
51	9	0.03	98.26
64	22	0.08	98.34
66.56	3	0.01	98.35
68	1	0	98.35
101	4	0.01	98.37
103	15	0.05	98.42
106	2	0.01	98.42
161.28	1	0	98.43
166.4	10	0.03	98.46
168.96	13	0.04	98.51
169	155	0.53	99.04
196	13	0.04	99.08
499.2	4	0.01	99.1
640	1	0	99.1
660.48	6	0.02	99.12
716.8	3	0.01	99.13
992	54	0.19	99.32
1690	13	0.04	99.36
1984	168	0.58	99.94
1985	1	0	99.94
2016	7	0.02	99.97
2048	9	0.03	100
Total	29,068	100	

Table A2-Beer Purchases of Containers Greater than 12 and 18 Ounces by Year and DMA

Year	DMA	Total Beer Purchases (>12 oz)	Total Beer Purchases (>18 oz)
2008	Atlanta	87,300,000	25,200,000
2009	Atlanta	89,400,000	24,400,000
2010	Atlanta	116,000,000	33,200,000
2011	Atlanta	135,000,000	39,800,000
2008	Boston	25,200,000	12,100,000
2009	Boston	27,700,000	14,400,000
2010	Boston	36,000,000	20,500,000
2011	Boston	42,000,000	23,100,000
2008	Chicago	168,000,000	70,600,000
2009	Chicago	162,000,000	68,300,000
2010	Chicago	166,000,000	65,300,000
2011	Chicago	169,000,000	68,000,000
2008	Dallas	96,000,000	40,400,000
2009	Dallas	81,100,000	34,600,000
2010	Dallas	73,400,000	35,300,000
2011	Dallas	87,200,000	47,200,000
2008	Detroit	59,800,000	46,500,000
2009	Detroit	50,600,000	40,500,000
2010	Detroit	85,700,000	72,700,000
2011	Detroit	108,000,000	87,300,000
2008	Hartford	4,707,883	3,914,281
2009	Hartford	4,507,285	3,460,023
2010	Hartford	5,492,463	4,184,407
2011	Hartford	5,928,426	4,159,419
2008	Los Angeles	550,000,000	532,000,000
2009	Los Angeles	597,000,000	583,000,000
2010	Los Angeles	612,000,000	590,000,000
2011	Los Angeles	677,000,000	646,000,000
2008	Miami	280,000,000	47,600,000
2009	Miami	299,000,000	38,700,000
2010	Miami	285,000,000	41,000,000
2011	Miami	245,000,000	43,800,000
2008	New York	138,000,000	107,000,000
2009	New York	145,000,000	114,000,000
2010	New York	156,000,000	123,000,000
2011	New York	169,000,000	132,000,000
2008	San Francisco	112,000,000	108,000,000
2009	San Francisco	139,000,000	134,000,000
2010	San Francisco	157,000,000	151,000,000
2011	San Francisco	175,000,000	164,000,000
2008	Seattle	220,000,000	97,800,000
2009	Seattle	248,000,000	99,400,000
2010	Seattle	263,000,000	103,000,000
2011	Seattle	272,000,000	92,300,000
2008	Syracuse	41,800,000	15,700,000
2009	Syracuse	46,100,000	16,400,000
2010	Syracuse	54,900,000	17,900,000
2011	Syracuse	65,300,000	23,500,000

Table A3. Estimates for First Stage Regressions

	(1)	(2)
	First Stage Regression of Container12	**First Stage Regression of Container18**
Non-Alcohol-Related Accidents	0.006	0.003
	(0.012)	(0.017)
Beer Consumption	0.493***	0.533***
	(0.152)	(0.170)
Population	-3.077**	-3.496*
	(1.542)	(1.945)
Alcohol Consumption	0.868*	0.799
	(0.504)	(0.813)
Lag of Container12	0.667***	-
	(0.050)	-
Lag of Container18	-	0.672***
		(0.037)
Sample Size	612	612

All regressions include both DMA and year fixed effects. The sample size is 612 observations come from 12 DMAs, 4 years and 13 four months period in a year. Column 1 is estimated by ordinary least squares using the log of total beer purchases of containers greater than 12 oz. given DMA-year-month cell as a dependent variable. Instrument variable used is one time lag of the endogenous variable, *Container12*. Column 2 is also estimated by ordinary least squares. The dependent variable is *Container18*, total beer purchases of containers greater than 18 ounces. Instrument variable is one time lag of the endogenous variable, *Container 18*. Standard errors are in parentheses and are clustered at the DMA level to allow for arbitrary patterns in heteroskedasticity and correlation in errors over time in a given DMA. ***, **,* denote statistical significance at 1%, 5% and 10% level respectively.

Chapter 2: Minimum Wages and Youth Binge Drinking

Abstract

Binge drinking is associated with many health problems, including unintentional injuries, intentional injuries (e.g., domestic violence, sexual assault), unintended pregnancy, liver disease, etc. Moreover, high-volume episodic binge drinking is very prevalent among teenagers and young adults. Given that approximately 90% of the alcohol consumed by youth under the age of 21 in the United States is in the form of binge drinking (Murphy et al., 2012), understanding the determinants of binge drinking behavior, particularly among youth, is important from the perspective of health and policy. In this paper, we explore the relationship between youth binge drinking and an unanticipated determinate of this behavior, minimum wage laws. Using a fixed effects regression model, we observe a positive relationship between minimum wage increases and binge drinking among teenagers. We find that, after accounting for demographic characteristics, different types of risky behaviors, excise tax, state and time fixed effects, and time varying state effects, a $1 increase in minimum wage increases binge drinking among teenagers by approximately 9%. Our results support recent findings that minimum wage increases are positively associated with alcohol related accidents among teenagers (Adam et al., 2012). Findings suggest that authorities should consider the unexpected impacts that minimum wage increase may have on alcohol consumption among teens, and consider parallel policies to help mitigate potential negative consequences.

2.1 Introduction

Binge drinking, defined by the National Institute on Alcohol Abuse and Alcoholism (NIAAA) as "a pattern of drinking that brings a person's blood alcohol concentration (BAC) to 0.08 grams percent or above, and typically happens when men consume 5 or more drinks, and when women consume 4 or more drinks, in about 2 hours", is associated with many health problems, including unintentional injuries (e.g., car crashes, falls, drowning), intentional injuries (e.g., domestic violence, sexual assault), unintended pregnancy, liver disease, etc. (Center for Disease Control and Prevention (CDC) 2014). Moreover, high-volume episodic binge drinking is very prevalent among teenagers and young adults. Approximately 90% of the alcohol consumed by youth under the age of 21 in the United States is in the form of binge drinking (Murphy et al. 2012; OJJDP (Office of Juvenile Justice and Delinquency Prevention 2005). Hence, understanding the determinants of binge drinking behavior, particularly among youth, is important from the perspective of health and policy.

Observed patterns of binge drinking behavior of youth, coupled with the fact that binge drinkers are 14 times more likely to engage in alcohol-impaired driving than non-binge drinkers (Naimi et al. 2003), suggest that vehicle crashes are a particularly costly consequence of this risky behavior. It is well known that motor vehicle crashes are a leading cause of mortality among teenagers in the US (CDC 2013). According to Centers for Disease Control and Prevention (CDC), on average, seven teenagers were killed every day in motor vehicle crashes in 2010. Also, just as is the case with adults, alcohol plays an important role in this outcome. Teens are 17 times more likely to be in an accident when they are drunk versus sober (CDC 2012), and approximately one million teenagers drove while intoxicated in 2011 (CDC 2012). Consequently, even though all the states impose Minimum Legal Drinking Age Law (MLDA) to prevent teenagers to purchase alcohol, these statistics show that teenage driving while intoxicated is still a severe problem in the United States.

In this paper, we explore the relationship between youth binge drinking and an unanticipated determinate of this behavior, minimum wage laws. Previous researchers have often focused on the impact of policies aimed at reducing teenager drinking, such as MLDA (Wagenaar and Toomey 2002) and beer taxes (e.g. Ruhm 1996; Adams et al. 2012). However, given the significant percentage of teenagers that are impacted by minimum wages increases and recent research findings, it likely worthwhile to analyze how this seemingly unrelated policy may impact a teen's willingness to consume high volumes of alcohol. In particular, a recent paper by Adams et al. (2012) in the *Review of Economics and Statistics* identified an unanticipated impact of minimum wage increases on alcohol-related crashes involving teenagers. Specifically, the Adams et al. paper demonstrates that higher real minimum wages, perhaps by influencing disposable income, increase alcohol-related accidents involving teenagers. The suggestion of the Adams et al. (2012) research is that increases in minimum wages lead to more alcohol consumption by teenagers, which subsequently translates into more auto fatalities. While the identification utilized in their paper is compelling, the actual drinking behavior of teens following minimum wage increases was not studied specifically. Given the nature of the relationship between alcohol-related driving and binge drinking behavior (referenced above), one would expect the positive association between minimum wages and drunk driving to be driven by binge drinking activity. In this new paper we explicitly attempt to draw a clearer connection between minimum wage policy and teen alcohol consumption, in particular binge drinking. Using information on cross-state variation in minimum wages during the 1991-2011 period and individual level data from the National Youth Risk Behavior Survey (YRBS), we implement a fixed effects regression design to identify if changes in real minimum wages impact teen binge drinking. Our findings show that a $1 increase in the real minimum wage increases binge drinking on average by approximately 9% among teens 14-18 years old.

Results are robust to the inclusion of time and state fixed effects, controls for age, education, race, ethnicity, the presence of other risky behaviors such as daily smoking habit and general alcohol consumption behavior, as well as state policy variation, such as beer taxes. Additionally, estimates separated by gender indicate that the primary effect is largely driven by behavioral changes among teenage males.

The paper proceeds as follows. Section 2 provides background of the impact of minimum wage on teenagers' consumption habits, including a review of literature on this issue. Section 3 explains the impact of an increase in minimum wage on binge drinking as well as information about the data sources used. While section 4 discusses the results, section 5 concludes.

2.2 Background and Previous Literature

There are many papers in the related literature which investigate the impact of government policies targeting alcohol consumption (e.g. MLDA (Wagenaar and Toomey 2002), blood alcohol content thresholds (Hingson, Heeren and Winter 2000), higher alcohol taxes (Ruhm, 1996; Adams et al. 2012) etc.) on alcohol consumption and drunk driving accidents among both teenagers and adults. Beer taxes, for example, have been shown to be effective at reducing automobile fatalities (e.g. Ruhm 1996), in particular among teens (Adams et al. 2012). This outcome is consistent with the extensive literature that has demonstrated that teens are more elastic to cigarette taxes than adults, as well as basic economic theory regarding elasticity and budget constraints. However, given that approximately 22%-25% of employed teens work at (or below) the minimum wage and approximately another 30% work within a dollar more than the minimum wage, a meaningful percentage of teen incomes are potentially impacted by minimum wage increases as well (Current Population Study-ORG). Given that minimum wage increases would likely increase consumers' consumption possibilities, and that this impact would be stronger among teenagers, the expectation is that an increase in minimum wage would lead to an increase in alcohol consumption and subsequently lead to more traffic fatalities. This impact is well examined in the aforementioned paper by Adams et al. (2012), which found that increases in real minimum wages increased alcohol-related accidents among teens.

Nonetheless, the impact of minimum wages on alcohol consumption itself has not been well explored. Our current study examines this relationship, in particular the form of consumption most strongly linked to automobile fatalities, binge drinking. Given basic economic theory and the outcomes of related research, in particular Adams el al. (2012), we anticipate that a rise in the real minimum wage will increase binge drinking behavior among teenagers.

Of course, this argument is somewhat dependent on the assumption that teen workers who remain employed after a minimum wage increase will get an increase in earnings, and, at the population level, these earnings increases will not be offset by employment losses, leaving the aggregate impact on teenagers improved. However, research on the employment effects of minimum wages often yields conflicting conclusions (see Card 1992; Card and Krueger 1994; Addison, Blackburn and Cotti 2009; Dube et al. 2010; Neumark and Wascher 2008), leaving this outcome somewhat uncertain. Adams et al. (2012) address this issue in detail, using the range of findings from the existing minimum wage employment literature to demonstrate that the effect of a $1 increase in the minimum wage could impact aggregate teen income as little as a net zero change (if disemployment effects are large) to as much as an increase in millions of dollars per week in average sized states (if estimated employment effects of minimum wages are near zero, which is often the case). Moreover, even in a scenario where disemployment effects are more sizable, minimum wages should still affect the distribution of income among teenagers in a way that would likely increase the likelihood of increased expenditures on alcohol, specifically if the marginal propensity to consume alcohol is particularly high for teenagers (which is likely).

Furthermore, previous studies have shown a positive relationship between teenagers' income and alcohol consumption. According to a survey conducted by National Center on Addiction and Substance Abuse (2003), a small increase in teen income lead to approximately a doubling alcohol drinking incidence among teenagers. Additionally, research on the issue by Markowitz and Tauras (2009) presents evidence that higher individual income – either due to allowances or earnings – is associated with increased use of alcohol among teenagers. Conversely, other researchers have postulated that there may be an increase in teen consumption of alcohol due to stress/depression caused by job loss or due to their concerns about the possibility of losing their jobs in the future. This argument is supported by Arkes (2007) who finds that an increase in unemployment among teenagers leads to a rise in the number of days that they drink alcohol per month. Consequently, the overall impact of minimum wage increases may increase alcohol consumption regardless of the net employment effects.

Building off of the relevant literature, our paper estimates how minimum wages affect binge drinking habits of teenagers. Given that minimum wage laws change over time and across states, we can use this variation to identify the effects of these policies broadly.

2.3 Data and Methods

Data Sources

To explore the impact of minimum wage increase on alcohol consumption we utilize the national school-based Youth Risk Behavior Survey (YRBS) from 1991 to 2011, conducted by CDC. In particular, we utilize data from the years 1991, 1999, 2001 2003, 2005, 2007, 2009 and 2011. YRBS is an individual-level survey designed to monitor different types of risk behaviors (e.g. alcohol and drug use, tobacco use, unhealthy dietary behaviors, etc.) among U.S. children 14-18 years of age engaging in full-time education. The survey is typically conducted every other year, comprises a national school-based survey, as well as state and local surveys, hence state-level identifiers are available for most (46) states.[14] In particular, our dependent variable of interest is a self-reported count of binge drinking in the past 30 days, defined as how many days a participant reported drinking more than five alcoholic beverages.

The YRBS data also provide us with a rich set of demographic and behavioral controls to utilize in our empirical investigation. Specifically, we have information on participants' age, gender, education year, race, ethnicity, and their responses for other risky behaviors, such as whether respondents have ever smoked or they smoke daily and how many days they have drunk alcohol in their life. These behavioral controls are very useful as they can help to account for unobserved differences in trends in the relative riskiness of certain teen populations that may not be captured by the model specification otherwise.

There are a few important limitations of the using the YRBS data. First, there is no information on employment status or wages in the YRBS, so an examination of the effect of

[14] YBRS provides a repeated cross-section of teens from different states over time, it does not provide repeated information on the same teens.

minimum wage increases on binge drinking separately for those teens employed and not employed or wage level is not possible. Second, because the YRBS is a survey of teens engaged in full-time education, there is the potential that selection bias may impact estimates if changes in the minimum wage affect the distribution of teenagers who are enrolled in school. Lastly, there may be measurement error, as we are asking teens to self-report illegal behaviors, which may meaningfully impact outcomes.

We combine the YRBS data with minimum wage data for each state and year that we are able to match in our YRBS sample. Information on state minimum wage changes are reported in the January editions of the *Monthly Labor Review*. In the event the minimum wage is passed in the middle of a year, the new and old minimum wage levels are averaged based on the number of months of each year in effect. State level nominal minimum wages are reported in Appendix A. It is worth noting that among the 46 states in our sample, 17 states apply the Federal minimum wage, while 29 states had one or more changes in the state mandated minimum wage during our sample time frame. Nevertheless, given we are looking at real minimum wages, there is significant time and space variation available to us in the minimum wage policy variable, which can be utilized to identify the impact of minimum wages on binge drinking among youth. We also include excise tax for beer in each state-year to control for teenagers' price sensitivity and any correlation between these policy changes and minimum wage changes that may confound our estimates. Data on beer taxes for each state were collected from the Federation of Tax Administrators web site. Table 1 provides descriptive statistics for the range of variables utilized in our estimation process. Table 2 and Table 3 provide the same information broken out by gender.

Empirical Methodology

In order to isolate the impact of minimum wage increase on binge drinking, we utilize an estimation strategy based on the following specification:

$$Bingedrinking_{itw} = \beta_0 + \beta_1 Minwage_{ts} + \beta_2 Age_{its} + \beta_3 Education_{its} + \beta_4 Gender_{its} + \beta_5 Ethnicity_{its} + \beta_6 Race_{its} + \beta_7 Smokingdaily_{its} + \beta_8 Smokingever_{its} + \beta_9 Alcohollife_{its} + \beta_{10} Tax_{ts} + \beta_{11} T_t + \beta_{12} L_s + \beta_{13} T_t L_s + \mathcal{E}_{its} \qquad (1)$$

where subscript *i* denotes individuals taking the survey, *t* denotes year and *s* denotes state. T_t and L_s are the time and state fixed effects respectively. The inclusion of time and state fixed effects is important in our model as they allow us to control for persistent differences in binge drinking behavior across states which are time-invariant and differences in binge drinking habits that vary over time which are common in all the states. In addition, we include T_tL_s which accounts for potential differences in uncaptured state time trends across locations.

Our dependent variable, $Bingedrinking_{itw}$, is the number of binge drinking events that each survey respondent reported undertaking in the last 30 days. Our policy variable of interest is $Minwage_{ts}$, which is annual minimum wage for each state in 2011 dollars. Additionally, we control for individual specific demographics such as Age_{its} *(age of the respondent)*, $Education_{its}$ *(year of education is 9, 10, 11, 12)*, $Gender_{its}$ *(male or female)*, $Ethnicity_{its}$ *(hispanic or not)*, $Race_{its}$ *(white, black, or other).* Hence, β_1 reports the marginal impact of a minimum wage increase on teenage binge drinking.

We understand that our empirical strategy must isolate the impact of a minimum wage increase on binge drinking aside from the other determinants of binge drinking. Hence, we also include measures of other risky behaviors, such as $Smokingdaily_{its}$ *(whether they smoke every day or not)*, $Smokingever_{its}$ *(whether they have smoked ever or not)*, $Alcohollife_{its}$ *(how many days they* *have drunk in their life),* to account for differences across individuals in their natural tendency to engage in risky behaviors. By controlling these variables, we should also be able to capture differences in binge drinking behavior that vary across participants due to differences in family education, income, home life, or general level of income allowance that these teens receive from their parents which might have an effect on teenagers' binge drinking behavior during the time period under investigation.

The final detail of our estimation of equation (1) concerns the distributional shape of binge drinking. Given that binge drinking counts are discrete in nature and suffer from over-dispersion, estimating equation (1) with an unconditional fixed effects negative binomial regression method would be standard (Hausman et al. 1984, Allison and Waterman 2002).[15] However, as demonstrated in Table 1, there is a large probability mass at zero binge drinking events. Theory suggests that the excess zeros are potentially generated by a separate process from the count values and that the excess zeros should be modeled independently using a zero-inflated negative binomial (ZINB) specification, which we investigate as well. Vuong (1989) tests of model fit fail to demonstrate a superior fit of the zero-inflated model compared to the simpler negative binomial specification.[16] Nevertheless, given the high mass of observations with zero accidents, we will demonstrate that results are robust to using the ZINB approach.

All inference of estimates in equation (1) is based on standard errors that have been corrected to allow for non-independence of observations from the same state through clustering

[15] Allison and Waterman (2002) demonstrate that a conditional likelihood method for negative binomial regression does not qualify as a true fixed effects method because it does not control for unchanging covariates, hence an unconditional estimation of a fixed effects negative binomial model is needed.

[16] In all cases the p-value is large and negative. These findings suggest that the zero-inflated model is indistinguishable from the non-zero-inflated-analog; indicating that excess zeros are not likely generated by a separate process from the count values.

(Arellano 1987, Bertrand et al. 2004). Statistical analyses were conducted using STATA version 13 (StataCorp, College Station, TX).

2.4 Empirical Results

Table 4 presents estimation results for the fixed-effects negative binominal model with number of binge drinking events in the last 30 days as the dependent variable. Results are reported as incidence rate ratios (IRR) and the corresponding p-values are in brackets. IRRs are the exponentiated coefficients and indicate the difference in binge drinking predicted by the model when a variable of interest is increased by one unit above its mean value while all other variables are kept constant at their means (see Table 1 for the summary statistics). An IRR value greater than one reflects a positive relationship between binge drinking and the particular independent variable, while a value less than one suggests a negative association. Statistical significance is based on a test of the null hypothesis that there is no relationship between binge drinking and the control variable (i.e., IRR is equal to one). Column (1) in Table 4 provides the result using only state and time fixed effects (no other controls). The estimate of β_1 is positive (1.10) and statistically significant (p-value = 0.033). Estimates indicate that a $1 increase in the real minimum wage results in a 10% increase in binge drinking behavior.

In the second through fourth columns of table 4 we sequentially add controls for demographic characteristics (e.g. age, gender, education, etc.), reported risky behaviors and beer tax rates. It may be the case that some of the right hand side variables in the regression (e.g. education, smoking, etc.) may also be impacted by changes to minimum wages: hence the coefficient on the minimum wage variable might not be picking up the full impact of changes to the minimum wage and demonstrating the results in this fashion is useful. Results are very consistent across specifications and progressively improved significance (p-value==0.000). Given the inclusion of new information, it is often useful to evaluate the sensitivity of the estimates on the other covariates included. In looking at these controls specifically, we observe that the estimated effects are as one would anticipate: older teens, males, and teens who engage in other risky behaviors engage in binge drinking most frequently.

The identification strategy explained to this point predicts that after inclusion of state and time fixed effects, demographic characteristics, and different risky behaviors, we will be able to estimate the impact of changes in the minimum wage on binge drinking habits accurately. One concern, however, is that changes in minimum wage laws might be correlated with some unobserved trends in binge drinking behaviors. While we don't suspect that this is an issue, in column (5) we move to our preferred specification and include state-specific time trends (*TtLs*) into the model. This specification should account for potential differences in uncaptured trends in binge drinking across locations. As is evident, the primary measure of interest is very similar (coefficient = 1.09, p-value=0.018), and provides the same inference that increases in the real minimum wage are associated with increased binge drinking activity in teens.[17,18]

Next, we extend our initial analysis to an investigation of differences between genders. The literature has demonstrated that the prevalence of binge drinking among men is twice that observed in women (e.g., Naimi T.S. et al. 2003; Nolen Hoeksema S. 2004). Hence, we would expect the impact of minimum wages on binge drinking to be larger among males if the results are sensible. To explore this difference explicitly, in the columns (1) and (2) of Table 5 we re-estimate the results provided in column (5) of Table 4 but for males and females separately. While the estimates

---

[17] Results are robust to using a zero-inflated negative binominal approach, with participant age and smoking habits used as the inflators. See Appendix B.
[18] Results are robust to excluding 1991 from the sample.

are positive in both cases, it is evident that the relationship estimates presented in Table 5 are driven by the males in the sample (p-value==0.002). Estimates suggest that a $1 increase in minimum wage results in a 12% increase in binge drinking for males, with much smaller and insignificant results for females. These outcomes improve confidence that the estimated relationship is a causal one.

Lastly, as a small extension, we attempt to provide greater insights if it is employed teens that are impacting outcomes. Specifically, if we assume that the primary channel through which minimum wages impact binge drinking is by increasing incomes among working teens, then one would expect the measured effect to be zero if we were able to restrict our sample to those teens who are not employed. Unfortunately, we do not have information on the work status of the teens to effectively capitalize on in the YBRS sample. Nevertheless, as a second best alternative, a specification which included an interaction between the minimum wage and the proportion of teenagers working at or around the minimum wage in the relevant state and time period may also provide some insights in this area. With this in mind we collected CPS Outgoing Rotation Group data for the years that match our YBRS sample, and constructed the percentage of working teens in each state-year that are working at or around the prevailing minimum wage in their state of residence (no more than $1 above and $2 above, separately). Next, we re-specify our initial model by including this proportion and an interaction between the proportions with the minimum wage variable of interest. Results are mixed and generally do not provide tremendous inference (see Appendix C). Specifically, when interacting with the share earning less than $1 above the minimum wage, the IRR estimates are approximately 1.00 in the full specification, suggesting no difference as the share impacted varies. On the other hand, when the share is defined as teens earning less than $2 above the minimum wage, the IRR estimates on the interaction range from

1.14 to 1.30, which suggests that as the portion of the working teen population that earns at or around minimum wage rises, the impact of a minimum wage increase on binge drinking is estimated to be meaningfully stronger. Nevertheless, none of these estimates are statistically significant, so it is difficult to draw meaningful conclusions from these estimates.

2.5 Conclusion

Given the large negative consequences associated with excessive alcohol consumption, understanding the effects of government policies aimed at lowering alcohol consumption and alcohol-related accidents has been an important topic of research for some time. However, until recently, studying the impact of policies that don’t directly target alcohol-related outcomes has not been investigated strongly. In this case, we investigate the impact that polices aimed at increasing population income, through minimum wage increases, which may have on binge drinking behavior among teens. Results provide evidence that an increase in minimum wages is positively associated with binge drinking activity among teenagers, specifically males. These results are robust to the inclusion of time and state fixed effects, controls for age, education, race, ethnicity, the presence of other risky behaviors such as daily smoking habit and general alcohol consumption behavior, and states beer taxes.

The findings presented here are consistent with the results presented in Adams et al. (2012), which identified that increases in real minimum wages lead to increases in alcohol-related accidents among teenagers. Different from the previous research on the issue, this paper attempts to explicitly investigate the impact of this policy change on the underlying behavior of interest, alcohol-consumption. Hence, provides a more meaningfully understand how increases in minimum wages potentially lead to increased alcohol-related fatalities among teens and impact the general relationship that exists between teenagers and minimum wages. We are also able to isolate that this effect is, at a minimum, stronger among males, which is consistent with the general observation that males are much more likely to binge drink than females.

That said, results should be informed by potential limitations of the YRBS data. First, there is no information on employment (or related factors) in the YRBS, so an examination of the effect of minimum wage increases on binge drinking separately for those teens employed and not employed (or by earnings) is not feasible. Second, because the YRBS is a survey full-time students, selection bias may impact results if minimum wages impact teen drop-out rates. Lastly, there may be measurement error, as teens are asked to self-report illegal behaviors, which may meaningfully impact outcomes.

Nevertheless, given the high costs associated with excessive alcohol consumption and the particularly high propensity for risk taking activities associated with teenagers, governmental bodies should be caution and cognizant of the negative consequences that such polices may have on teen behaviors. That said, our results should not be interpreted as a denunciation of minimum wage policies, but rather as a quantitative analysis of how teenagers respond to exogenous changes in disposable income. As such, public policy leaders might consider implementing corresponding measures alongside an increase in minimum wages that would help to mitigate potentially harmful behavioral responses observed in teenagers, such as increased taxation on beer. At the least, local officials should recognize the potential need for careful implementation of increased minimum wages. The Federal government already has a limited provision for a “youth minimum wage”, but this policy only applies for the first 90 days of employment. Many states have similar policies as well. Given the results presented here and in related studies, perhaps it would be useful to consider more meaningful youth minimum wage restrictions or related constraints to help offset potentially negative health behaviors.

References

Adams Scott, Blackburn L. McKinley, and Cotti D. Chad (2012) Minimum wages and alcohol-related traffic fatalities among teens. The Review of Economics and Statistics 94(3): 828-840.

Addison T. John, Blackburn L. McKinley, and Cotti D. Chad (2009) Do minimum wages raise employment? Evidence from the U.S. retail-trade sector. Labour Economics 16:4, 397–408.

Allison D. Paul, and Waterman P. Richard (2002) Fixed-effects negative binomial regression models. Sociological Methodology 32, 247-265.

Arellano M. (1987) Computing robust standard errors for within-group estimators. Oxford Bulleting of Economics and Statistics 49, 4, 0305-9049.

Arkes Jeremy (2007) Does the economy affect teenage substance use? Health Economics 16:1, 19–36.

Bertrand M., Duflo E. and Mullainathan S. (2004) How much should we trust difference in differences estimates? The Quarterly Journal of Economics 119 (1): 249-275.

Card D (1992) Do minimum wages reduce employment? A case study of California 1987–1989. Industrial and Labor Relations Review 46:22–37.

Card D, and Krueger B. Alan (1994) Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania. American Economic Review 84:772–793.

Centers for Disease and Control Prevention (2012) Teen Drinking and Driving – A Dangerous Mix: http://www.cdc.gov/vitalsigns/TeenDrinkingAndDriving/index.html

Centers for Disease Control and Prevention(2013) Ten Leading Causes of Death and Injury: http://www.cdc.gov/injury/wisqars/leadingcauses.html

Centers for Disease Control and Prevention (2014) Fact Sheets - Binge Drinking: http://www.cdc.gov/alcohol/fact-sheets/binge-drinking.htm

Current Population Study – ORG: http://www.nber.org/data/morg.html

Dube Arindrajit, Lester T. William, and Reich Michael (2010) Minimum wage effects across state borders: Estimates using contiguous counties. The Review of Economics and Statistics 92(4): 945-64.

Hausman Jerry, Hall H. Bronwyn, Griliches Zvi (1984) Econometric models for count data with applications to the patents R and D relationship. Econometrica 52: 909-938.

Hingson Ralph, Heeren Timothy, and Winter Michael (2000) Effects of recent 0.08% legal blood alcohol limits on fatal crash involvement. Injury Prevention 6, 109-114.

Hoeksema N. Susan (2004) Gender differences in risk factors and consequences for alcohol use and problems. Clinical Psychology Review 24:981.

Markowitz Sara, and Tauras John (2009) Substance use among adolescent students with consideration of budget constraints. Review of Economics of the Household 7:4, 423–446.

Murphy G. James et al. (2012) A behavioral economic supplement to brief motivational interventions for college drinking. Addiction Research Theory 20(6), 456-465.

National Center on Addiction and Substance Abuse (2003) National survey of American attitudes on substance abuse VIII: Teens and parents. New York: Columbia University.

Neumark David and Wascher L. William (2008) Minimum wages. Cambridge, MA: The MIT Press.

Office of Juvenile Justice and Delinquency Prevention (OJJDP) (2005) *Drinking in America: Myths, realities, and prevention policy* .Washington, DC: U.S. Department of Justice, Office of Justice Programs, Office of Juvenile Justice and Delinquency Prevention.

Ruhm J. Christopher (1996) Alcohol policies and highway vehicle fatalities. Journal of Health Economics 15(4), 435–454.

Timothy S. Naimi et al. (2003) Binge drinking among U.S. adults. Journal of the American Medical Association 289(1):70–75.

Vuong H. Quang (1989) Likelihood ratio rests for model selection and non-nested hypotheses. Econometrica 57/2, 307-333.

Wagenaar C. Alexander, and Toomey L. Traci (2002) Effects of minimum drinking age laws: review and analyses of the literature from 1960 to 2000. Journal of Studies on Alcohol Supplement No: 14:206–225.

TABLE 1.- STATE LEVEL DESCRIPTIVE STATISTICS

Variable	Obs	Mean	Std. Dev.	Min	Max	Percent
Binge Drinking (# of days having more than 5 drinks in last 30 days)	97,412	1.66	3.87	0	20	
Real Minimum Wage in 2011 dollars	97,412	6.80	0.76	5.77	8.82	
Number of the days the respondent drunk alcohol in her/his life	97,412	24.05	33.61	0	100	
Real Excise Tax in 2011 dollars	97,412	0.29	0.19	0.06	1.20	
Dummy Variables						
Age Groups						
14 years old	97,412					9.17
15 years old	97,412					22.28
16 years old	97,412					25.90
17 years old	97,412					26.16
18 years old	97,412					16.48
if gender is male	97,412					48.56
education year==9	97,412					24.14
education year==10	97,412					24.71
education year==11	97,412					25.48
education year==12	97,412					25.67
if ethnicity is Hispanic	97,412					26.65
if race is white	97,412					48.39
if race is black	97,412					21.15
if race is other	97,412					30.46
if smoking daily	97,412					14.07
if smoked ever	97,412					58.40

TABLE 2.-STATE LEVEL DESCRIPTIVE STATISTICS FOR MALES

Variable	Obs	Mean	Std. Dev.	Min	Max	Percent
Binge Drinking (# of days having more than 5 drinks in last 30 days)	47,306	2.02	4.35	0	20	
Real Minimum Wage in 2011 dollars	47,306	6.80	0.76	5.77	8.82	
Number of the days the respondent drunk alcohol in her/his life	47,306	27.59	36.19	0	100	
Real Excise Tax in 2011 dollars	47,306	0.28	0.19	0.06	1.20	
Dummy Variables						
Age Groups						
14 years old	47,306					8.24
15 years old	47,306					21.50
16 years old	47,306					25.68
17 years old	47,306					26.48
18 years old	47,306					18.10
education year==9	47,306					23.95
education year==10	47,306					24.57
education year==11	47,306					25.46
education year==12	47,306					26.02
if ethnicity is Hispanic	47,306					26.46
if race is white	47,306					49.40
if race is black	47,306					20.13
if race is other	47,306					30.47
if smoking daily	47,306					15.13
if smoked ever	47,306					60.29

TABLE 3.-STATE LEVEL DESCRIPTIVE STATISTICS FOR FEMALES

Variable	Obs	Mean	Std. Dev.	Min	Max	Percent
Binge Drinking (# of days having more than 5 drinks in last 30 days)	50,106	1.32	3.32	0	20	
Real Minimum Wage in 2011 dollars	50,106	6.80	0.76	5.77	8.82	
Number of the days the respondent drunk alcohol in her/his life	50,106	20.71	30.60	0	100	
Excise Tax	50,106	0.29	0.19	0.1	1.20	
Dummy Variables						
Age Groups						
14 years old	50,106					10.05
15 years old	50,106					23.02
16 years old	50,106					26.1
17 years old	50,106					25.86
18 years old	50,106					14.96
education year==9	50,106					24.32
education year==10	50,106					24.84
education year==11	50,106					25.5
education year==12	50,106					25.34
if ethnicity is Hispanic	50,106					26.83
if race is white	50,106					47.43
if race is black	50,106					22.12
if race is other	50,106					30.45
if smoking daily	50,106					13.06
if smoked ever	50,106					56.63

TABLE 4--NEGATIVE BINOMIAL ESTIMATES FOR THE DETERMINANTS OF BINGE DRINKING AMONG TEENAGERS AGED 14-18

	1	2	3	4	5
VARIABLES	**FE ONLY**	**FE+DEMOG**	**ADD EDUCATION**	**FULL SPEC**	**FULL + TRENDS**
Real minimum wage in 2011 dollars	1.10**	1.08**	1.08**	1.13***	1.09**
	[0.033]	[0.025]	[0.024]	[0.000]	[0.018]
Dummy variable for age 14		0.44***	0.52***	0.77***	0.77***
		[0.000]	[0.000]	[0.000]	[0.000]
Dummy variable for age 15		0.52***	0.61***	0.85***	0.85***
		[0.000]	[0.000]	[0.000]	[0.000]
Dummy variable for age 16		0.70***	0.79***	0.91***	0.91***
		[0.000]	[0.000]	[0.000]	[0.001]
Dummy variable for age 17		0.84***	0.89***	0.93***	0.93***
		[0.000]	[0.001]	[0.000]	[0.001]
If male		1.59***	1.60***	1.10***	1.10***
		[0.000]	[0.000]	[0.000]	[0.000]
Ethnicity if Hispanic		1.20*	1.20*	1.17***	1.17***
		[0.037]	[0.038]	[0.000]	[0.000]
Race if white		1.36***	1.35***	1.14***	1.13***
		[0.000]	[0.000]	[0.000]	[0.000]
Race if black		0.60***	0.61***	0.88*	0.88*
		[0.000]	[0.000]	[0.014]	[0.017]
Education year==10 grade			1.06	1.03	1.03
			[0.096]	[0.259]	[0.259]
Education year==11 grade			1.10*	1.03	1.03
			[0.043]	[0.533]	[0.515]
Education year==12 grade			1.22***	0.98	0.99
			[0.001]	[0.734]	[0.778]
If smoking daily				1.35***	1.35***
				[0.000]	[0.000]
If smoked ever				2.11***	2.11***
				[0.000]	[0.000]
Number of days drunk alcohol in his life				1.03***	1.03***
				[0.000]	[0.000]
Real excise tax in 2011 dollars				0.61	1.51
				[0.306]	[0.274]
Observations	97,412	97,412	97,412	97,412	97,412
State and Year FE	**YES**	**YES**	**YES**	**YES**	**YES**
State Time Trends	**NO**	**NO**	**NO**	**NO**	**YES**

All models use a negative binomial approach. Results show the Incidence Rate Ratio (IRR) and P-values are given in parenthesis. The dependent variable is binge drinking which is based on the answer given by YRBS survey respondents to the question "During the past 30 days, on how many days did you have 5 or more drinks of alcohol in a row, that is, within a couple of hours?" The dependent variable is survey takers responses in a given state-year cell. Standard errors are clustered at the state level to allow for arbitrary patterns in heteroskedasticity and correlation in errors over time in a given state. ***, **,* denote statistical significance at 1%, 5% and 10% level respectively.

TABLE 5--NEGATIVE BINOMIAL ESTIMATES FOR THE DETERMINANTS OF BINGE DRINKING AMONG TEENAGERS AGED 14-18, Males and Females

	1	2
VARIABLES	**Males**	**Females**
Real minimum wage in 2011 dollars	1.12***	1.05
	[0.002]	[0.213]
Dummy variable for age 14	0.71***	0.85
	[0.000]	[0.090]
Dummy variable for age 15	0.83***	0.9
	[0.000]	[0.164]
Dummy variable for age 16	0.91**	0.95
	[0.003]	[0.340]
Dummy variable for age 17	0.94**	0.93*
	[0.003]	[0.040]
If male		
Education year==10 grade	1.02	1.02
	[0.576]	[0.559]
Education year==11 grade	1.06	0.98
	[0.206]	[0.841]
Education year==12 grade	1.03	0.95
	[0.553]	[0.578]
Ethnicity if Hispanic	1.16**	1.19***
	[0.002]	[0.001]
Race if white	1.09**	1.18***
	[0.007]	[0.000]
Race if black	0.93	0.83*
	[0.111]	[0.013]
If smoking daily	1.35***	1.35***
	[0.000]	[0.000]
If smoked ever	2.03***	2.23***
	[0.000]	[0.000]
Number of days drunk alcohol in his life	1.03***	1.03***
	[0.000]	[0.000]
Real excise tax in 2011 dollars	1.65	1.34
	[0.363]	[0.620]
Observations	47,306	50,106
State and Year FE	**YES**	**YES**
State Time Trends	**YES**	**YES**

All models use a negative binomial approach. Results show the Incidence Rate Ratio (IRR) and P-values are given in parenthesis. The dependent variable is binge drinking which is based on the answer given by YRBS survey respondents to the question " During the past 30 days, on how many days did you have 5 or more drinks of alcohol in a row, that is, within a couple of hours?" The dependent variable is survey takers responses in a given state-year cell. Standard errors are clustered at the state level to allow for arbitrary patterns in heteroskedasticity and correlation in errors over time in a given state. ***, **,* denote statistical significance at 1%, 5% and 10% level respectively.

APPENDIX A
Nominal Minimum Wages by State and Year (in dollars), 1991-2011

State	1991	1999	2001	2003	2005	2007	2009	2011
ALABAMA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
ALASKA	4.75	5.65	5.65	7.15	7.15	7.15	7.18	7.75
ARIZONA	4.14	5.15	5.15	5.15	5.15	6.75	7.25	7.35
ARKANSAS	4.14	5.15	5.15	5.15	5.15	6.25	6.84	7.25
CALIFORNIA	4.25	5.75	6.25	6.75	6.75	7.50	8.00	8.00
COLORADO	4.14	5.15	5.15	5.15	5.15	6.85	7.28	7.36
CONNECTICUT	4.27	5.65	6.40	6.90	7.10	7.65	8.00	8.25
DELAWARE	4.14	5.44	6.15	6.15	6.15	6.65	7.18	7.25
FLORIDA	4.14	5.15	5.15	5.15	5.82	6.67	7.22	7.29
GEORGIA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
HAWAII	4.15	5.25	5.25	6.25	6.25	7.25	7.25	7.25
IDAHO	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
ILLINOIS	4.14	5.15	5.15	5.15	6.50	7.00	7.88	8.25
INDIANA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
IOWA	4.25	5.15	5.15	5.15	5.15	5.94	7.25	7.25
KANSAS	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
KENTUCKY	4.14	5.15	5.15	5.15	5.15	5.44	6.90	7.25
LOUISIANA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
MAINE	4.15	5.15	5.15	6.25	6.39	6.81	7.31	7.50
MARYLAND	4.14	5.15	5.15	5.15	5.15	6.15	6.84	7.25
MASSACHUSETTS	4.14	5.25	6.75	6.75	6.75	7.50	8.00	8.00
MICHIGAN	4.14	5.15	5.15	5.15	5.15	7.05	7.40	7.40
MINNESOTA	4.18	5.15	5.15	5.15	5.40	6.15	6.84	7.25
MISSISSIPPI	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
MISSOURI	4.14	5.15	5.15	5.15	5.15	6.50	7.10	7.25
MONTANA	4.14	5.15	5.15	5.15	5.15	5.44	7.02	7.35
NEBRASKA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
NEVADA	4.14	5.15	5.15	5.15	5.15	6.15	6.84	8.25
NEW HAMPSHIRE	4.15	5.15	5.15	5.15	5.15	5.61	7.25	7.25
NEW JERSEY	4.14	5.15	5.15	5.15	5.40	7.15	7.18	7.25
NEW MEXICO	4.14	5.15	5.15	5.15	5.15	5.44	7.50	7.50
NEW YORK	4.14	5.15	5.15	5.15	6.00	7.15	7.18	7.25
NORTH CAROLINA	4.14	5.15	5.15	5.15	5.15	6.15	6.84	7.25
NORTH DAKOTA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
OHIO	4.14	5.15	5.15	5.15	5.15	6.85	7.30	7.40
OKLAHOMA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
OREGON	4.75	6.50	6.50	6.90	7.25	7.80	8.40	8.50
PENNSYLVANIA	4.14	5.15	5.15	5.15	5.15	6.70	7.18	7.25
RHODE ISLAND	4.45	5.40	6.15	6.15	6.75	7.40	7.40	7.40

SOUTH CAROLINA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
SOUTH DAKOTA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
TENNESSEE	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
TEXAS	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
UTAH	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
VERMONT	4.18	5.38	6.25	6.25	7.00	7.53	8.06	8.15
VIRGINIA	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25
WASHINGTON	4.25	5.70	6.72	7.01	7.35	7.93	8.55	8.67
WEST VIRGINIA	4.14	5.15	5.15	5.15	5.15	6.55	7.25	7.25
WISCONSIN	4.14	5.15	5.15	5.15	5.47	5.74	6.84	7.25
WYOMING	4.14	5.15	5.15	5.15	5.15	5.44	6.84	7.25

Source: January Edition of the Monthly Labor Review. Minimum wage values reflect the monthly average nominal minimum wage for every state and every year. Minimum wage values used for estimation in the paper are adjusted to 2011 GDP deflator to correct for inflation.

APPENDIX B

ZERO INFLATED NEGATIVE BINOMIAL: ESTIMATES FOR THE DETERMINANTS OF BINGE DRINKING AMONG TEENAGERS AGED 14-18

VARIABLES	ZINB
Real minimum wage in 2011 dollars	1.09***
	[0.000]
Dummy variable for age 14	0.81***
	[0.000]
Dummy variable for age 15	0.87***
	[0.000]
Dummy variable for age 16	0.92***
	[0.001]
Dummy variable for age 17	0.93***
	[0.000]
If male	1.10***
	[0.000]
Education year==10 grade	1.03
	[0.202]
Education year==11 grade	1.03
	[0.320]
Education year==12 grade	0.98
	[0.587]
Ethnicity if Hispanic	1.17***
	[0.000]
Race if white	1.13***
	[0.000]
Race if black	0.88***
	[0.000]
If smoking daily	1.32***
	[0.000]
If smoked ever	2.10***
	[0.000]
Number of days respondent drunk alcohol in his life	1.03***
	[0.000]
Real Excise Tax in 2011 dollars	1.51
	[0.217]
State and Year FE	Yes
State Time Trend	Yes
Observations	97,412
Z score	-4.49
P Value	1.00

Results show the Incidence Rate Ratio (IRR) and P-values are given in parenthesis. Our dependent variable is binge drinking: The answer of YRBS survey respondents for the question of "how many days have they had more than 5 drinks in last 30 days?". The dependent variable is survey takers responses in a given state-year cell. ***, **,* denote statistical significance at 1%, 5% and 10% level respectively.

APPENDIX C

NEGATIVE BINOMIAL ESTIMATES FOR THE DETERMINANTS OF BINGE DRINKING AMONG TEENAGERS AGED 14-18; ESTIMATES INCLUDING INTERACTIONS WITH THE PROPORTION OF TEEN WORKERS NEAR MINIMUM WAGE

	1	2	3	4
VARIABLES	**FULL SPEC**	**FULL + TRENDS**	**FULL SPEC**	**FULL + TRENDS**
Real minimum wage in 2011 dollars	1.08**	1.08**	1.13***	1.09**
	[0.025]	[0.024]	[0.000]	[0.018]
Proportion of working teens wage near MW#	0.83	1.06	0.17	0.34
	[0.836]	[0.958]	[0.252]	[0.532]
Interaction: Real MW * Proportion near MW#	1.02	0.98	1.30	1.14
	[0.919]	[0.885]	[0.300]	[0.640]
Dummy variable for age 14	0.77***	0.77***	0.77***	0.77***
	[0.000]	[0.000]	[0.000]	[0.000]
Dummy variable for age 15	0.85***	0.85***	0.85***	0.85***
	[0.000]	[0.000]	[0.000]	[0.000]
Dummy variable for age 16	0.91***	0.91***	0.91***	0.91***
	[0.000]	[0.001]	[0.000]	[0.001]
Dummy variable for age 17	0.93***	0.93***	0.93***	0.93***
	[0.000]	[0.001]	[0.001]	[0.001]
If male	1.10***	1.10***	1.10***	1.10***
	[0.000]	[0.000]	[0.000]	[0.000]
Ethnicity if Hispanic	1.17***	1.17***	1.17***	1.17***
	[0.000]	[0.000]	[0.000]	[0.000]
Race if white	1.14***	1.13***	1.14***	1.13***
	[0.000]	[0.000]	[0.000]	[0.000]
Race if black	0.88*	0.88*	0.88*	0.88*
	[0.014]	[0.016]	[0.015]	[0.017]
Education year==10 grade	1.03	1.03	1.03	1.03
	[0.258]	[0.259]	[0.257]	[0.258]
Education year==11 grade	1.03	1.03	1.03	1.03
	[0.533]	[0.517]	[0.531]	[0.514]
Education year==12 grade	0.98	0.99	0.98	0.99
	[0.731]	[0.773]	[0.727]	[0.774]
If smoking daily	1.35***	1.35***	1.35***	1.35***
	[0.000]	[0.000]	[0.000]	[0.000]
If smoked ever	2.11***	2.11***	2.11***	2.11***
	[0.000]	[0.000]	[0.000]	[0.000]
Number of days drunk alcohol in his life	1.03***	1.03***	1.03***	1.03***
	[0.000]	[0.000]	[0.000]	[0.000]
Real excise tax in 2011 dollars	0.61	1.46	0.55	1.49
	[0.302]	[0.293]	[0.224]	[0.304]
Observations	97,412	97,412	97,412	97,412
State and Year FE	**YES**	**YES**	**YES**	**YES**
State Time Trends	**NO**	**NO**	**NO**	**YES**

All models use a negative binomial approach. Results show the Incidence Rate Ratio (IRR) and P-values are given in parenthesis. The dependent variable is binge drinking which is based on the answer given by YRBS survey respondents to the question "During the past 30 days, on how many days did you have 5 or more drinks of alcohol in a row, that is, within a couple of hours?" The dependent variable is survey takers responses in a given state-year cell. Standard errors are clustered at the state level to allow for arbitrary patterns in heteroskedasticity and correlation in errors over time in a given state. # In columns 1 and 2, proportion corresponds to no more than $1 above the prevailing minimum wage in any state-year. In columns 3 and 4, proportion corresponds to no more than $2 above the prevailing minimum wage in any state-year ***, **,* denote statistical significance at 1%, 5% and 10% level respectively.

Chapter 3: Product Line Depth and Shelf Space Competition in the U.S. Beer Industry

Abstract

Product variety has been an important topic not only for the firms but also for the researchers for last decades. While firms have been increasing product variety to maximize their profit, researchers have been trying to explore its effect on economic outcomes. Previous empirical research has focused mainly on the effects of managing product line length, which measures the number of total products or items in a firms product mix. In this paper, we explicitly examine product line depth, which measures the number of variations of a specific product: creating different sizes or packages of the same product. To examine effect of product line depth on consumer demand and firm performance, we formulate an econometric model that considers both consumer choices and firm strategies of product line depth decisions, using product-level scanner data in the U.S. beer industry. On the demand side, we formulate and estimate a product-level discrete choice model and include a measure of product line depth in the utility function to investigate consumer preference for variety. On the supply side, oligopolistic firms compete in both prices and product line depth, and maximize their profits. Our results suggest that while an increase in package size variety for bottles orcans brings an increase in market share, after a threshold there are diminishing returns. Further, the simulation results suggest that for firms in the beer industry, an optimal product line depth strategy is to extend the product line depth by providing more package size options than container size options.

3.1 Introduction

Increased product variety can benefit consumers as it more closely matches the needs of particular market segments. By extending their product line, a firm may therefore increase their overall market demand (Bayus and Putsis 1999) and potentially their profits as well (Tremblay and Tremblay 2005). By actively managing product lines, managers may also be able to better address competitive pressures (Draganska and Jain 2005) and potentially deter entry by competitors (Bayus and Putsis 1999). Further, a greater variety of products may retain customer loyalty and allows firms to charge higher prices. Alternatively, extending a firm's product lines may have drawbacks, which could negatively impact overall profits. Extending product lines raises firm costs, which could negate any additional revenues (Bayus and Putsis 1999). While extending the line could increase demand, it could also lead to cannibalization of demand which could ultimately weaken the firm's brand (Quelch and Kenny 1994).

There is mixed empirical evidence regarding the impact of product line extension on firm performance. Kadiyali et al (1999) find that yogurt firms that extend their product line gain price-setting power (i.e. prices over marginal costs) and obtain increased sales. Kekre and Srinivasan (1990) find that US manufacturing firms gain market share benefits and increased profitability with broader product lines. More importantly, they find no empirical support for increased production costs. While Draganska and Jain (2005) also find that product line length can lead to greater market share for yogurt firms, they identify decreasing returns to product-line length. Bayus and Putsis (1999) find a negative relationship between market share and product proliferation in the computer industry. They suggest that the cost increases associated with a broader product line dominate any potential demand increases. Anecdotal evidence further suggests that numerous retailers use product line reduction as a way to cut costs (Brant et al. 2009).

The previous empirical research has focused mainly on the effects of managing product line length, which measures the number of total products or items in a firms product mix. In this paper, we explicitly examine product line depth, which measures the number of variations of a specific product (Kotler and Keller 2009). For instance, creating different sizes or packages of the same product is an example of increasing product depth. This distinction is relevant for several reasons.

First, lengthening a product line requires greater investment in creating new products, which requires more time and investment. Further, these new products may ultimately compete directly in the marketplace for consumer demand, which could lead to cannibalization of a firm's own market share. Alternatively, increasing product depth does not require a new product, only a variation in how the product is delivered to the consumers. As such, there is less investment required. In addition, product competition is lessened since the product is virtually identical, save minor modifications to the existing product. Consequently, we might expect some of the previously expressed concerns regarding product line extension to be less relevant when analyzing product line depth.

To examine the impact of product line depth, we focus our research on the U.S. retail beer industry. This is a dynamic industry that has changed tremendously over the past four decades. Importantly, brewers often extend their product line length by introducing new product varieties into the market place under their parent company label. At the same time, most major macro breweries earn their greatest market share through their flagship beers.[19] For instance, while Annheuser-Busch has an extensive product line, the majority of their sales still come from Budweiser in the United States. Such emphasis on major flagship brands has allowed for

[19] A macro brewery is generally defined as any brewery making over 6 million barrels of beer per year.

opportunities to gain market share by extending product line depth. In particular, we find that brewers often invest in new packaging variations to appeal to consumers while maintaining the same product. For example, brewers can offer a single product using a variety of package sizes (e.g. 6 pack, 12 pack, 30 pack etc.), container types (cans, bottles or kegs), container sizes (e.g. 12, 15, 18, 24 ounces etc.) or any combinations of these. Extending the product line depth can be more cost effective and straightforward since no new product development is required. Further, by creating convenience for consumers seeking a particular package type, brewers may capture greater market share or potentially increase profits via price discrimination.

Within the *retail* beer market, there are two other important marketing benefits that may come from extending product depth. First, by offering a larger variety of packages, brewers can obtain more valuable shelf-space in grocery stores. Given limited shelf space, packages that can fit specific dimensions are more easily stocked. Further, by having a variety of package sizes in stores, brewers can create a type of billboard effect where their brand name is widely advertised across more space. Consider the image of a fully stocked beer section with a wall of *Budweiser* products extending across the majority of shelf space. Finally, if firms can successfully gain more shelf space by extending product depth, they may ultimately create barriers for new entrants into the market.

Clearly, the costs associated with extending product line depth are relevant, making the benefits of such managerial actions an empirical question. To date, we are unaware of other studies that explicitly examine the impact of product line depth on firms. In this paper, to examine effect of product line depth on consumer demand and firm performance, we formulate an econometric model that considers both consumer choices and firm strategies of product line depth decisions. On the demand side, we formulate and estimate a product-level discrete choice model and include a measure of product line depth in the utility function to investigate consumer preference for variety. On the supply side, oligopolistic firms compete in both prices and product line depth, and maximize their profits. A cost term of product length are introduced into firms' profit maximization problem following Draganska and Jain (2005).

Our results suggest that, while an increase in package size variety for bottles or cans brings an increase in market shares, after a threshold there are diminishing returns to increasing package variety. Further, the simulation results suggest that, for firms in beer industry, an optimal product line depth strategy is to extend the product line depth by providing more package size and container size options, but relatively more of the package size options.

The remainder of the paper proceeds as follows. Section 2 describe the data and summary statistics. Section 3 introduces the empirical model. Section 4 presents the estimation results and Section 5 concludes with a discussion of our analysis.

3.2 Data

The main dataset used in this analysis is the Nielsen Scanner Database (NSD), which gives a representative sample of purchase habits for different locations across the U.S. The NSD data is aggregated by Nielsen Designated Market Areas (DMAs), which are geographic areas defined by Nielsen Media Research Company. This analysis covers ten DMAs including Atlanta, Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York, San Francisco and Seattle. The frequency of observations is a rolling four-week block, which is defined as "monthly" for simplicity, from 2008 to 2012. NSD includes DMA level sales data for supermarkets, grocery stores, and drug stores with more than $2 million annual sales in the U.S., which consists of dollar sales, volume sales, and prices for beer products. In addition, it also provides detailed information on product characteristics (e.g. brand names, container sizes, package sizes, etc.), marketing (e.g. price and in-store displays), location and time of sales. The final data includes 47 brands from 15 companies.

We provide summary statistics for the full sample in Table 1. The average market share of a beer product in one DMA in a month is 0.43%. We calculate the market share of each beer product in our sample as a share of the total potential market size in the alcohol beverage market. Specifically, the potential market size is the combined per capita consumption (in volume) of all types of alcohol beverages including beer, wine and spirit times population in each market. Data on per capita alcohol consumption is collected from National Institute on Alcohol Abuse and Alcoholism.[20]

On average, the price per ounce of a beer product is $0.09. The price is calculated as sales-weighted prices over time, market, container size and package size. An average beer product has calories of 12.51 per ounce with the alcohol content of 0.42 per ounce. Of all beer products available on the market, around 64% of them are domestic beer and the rest of imported products.

In this analysis, product line depth offered by one brand is defined on two dimensions: container size variety and package size variety. For example, if a beer brand offers products in 6-pack, 12- pack and 18-pack in a market, then the package size variety for this brand is three. Similarly, if a beer brand offers 8 oz, 12 oz, 16 oz, 24 oz, and 36 oz beer products in a market, then product variety by size for this brand is five. Further, since most beer products offer in either can or bottle, we distinguish the size and package varieties by different materials: “package size variety

[20] http:/www.niaaa.nih.gov/

by can", "package variety size by bottle", "container size variety by can", "container size variety by bottle". On average, a beer brand owns a total of 7 different package offerings, 3.23 for canned beer and 3.88 for bottled beer. In terms of container size variety, an average beer brand offers 4 different sizes, 1.77 in cans and 2.39 in bottles. Overall, beer brands provide more variety options for bottled beer. We further provide summary statistics for canned and bottled beer separately. The average market share of a canned beer in a DMA is 0.53%, which is slightly higher than that of bottled beer. The unit price is higher for bottled beer while there is no significant difference of alcohol content and calories between the two types of beer products. The percentage of domestic product is significantly higher in canned beer.

We also provide summary statistics by different firm types in Table 2. In the beer market, there are three types of firms: mass producers, international brewers, and craft brewers[21]. Beer products offered by craft brewers are the most expensive ones, $0.12 per ounce on average, followed by international brewers and mass producers. Imported beers by international brewers enjoy the highest market share per DMA, which is around 0.74%. It is worth to notice that imported beers and craft beers are not available in every DMA so the numbers of observations are significantly lower than that of mass producers. The alcohol content and calories are similar across products from different types of firms. Mass producers offer a higher number of product variety both in packaging and size. Craft brewers, on the other hand, focus on bottled beers and a smaller set of product variety.

[21] Craft brewers are defined as producing fewer than 6 million barrels per year and having less than 25 percent ownership by a non-craft brewer.

3.3 Model and Estimation

Demand Side

We set up the demand side of our model as follows. Assume there are a total of *J* beer products on the market. In this analysis, a product is defined as a combination of a different brand, size, package and container type (bottle or can). For example, a 6-pack, 12-oz of Budweiser and a 12-pack, 12-oz of Budweiser are considered as different products.

A consumer *i* in market *d* chooses a product *j* from our choice set *j=1,...,*J at time t to maximize his utility. They are also given the choice of not buying beer but choosing an outside product in the beverage market (*j*=0). So the utility that a consumer *i* from purchasing beer *j* in market *d* at time *t* is given by

$$U_{ijdt} = \alpha_0 + \alpha_1 X_j + \alpha_2 p_{jdt} + \alpha_3 Variety_{jt} + \alpha_4 Variety_{jt}^2 + \xi_j + \epsilon_{ijdt} \qquad (1)$$

$$for\ all\ i = 1, \dots, N;\ \ j = 0,1, \dots, J;$$

where X_j is a vector of observed product characteristics of beer product *j.*, such as calories, alcohol content, style, type of the products, etc. $p_{jdt}$is the unit price per ounce of product *j* in market *d* at time *t*. The unit price and product characteristics is unique to each product.

$Variety_{jt}$ is the total number of product varieties, or product line length, of a brand to which product *j* belongs at time t, which is common across a given brand. The estimated coefficient will answer the question of interest: whether a brand benefit from offering a larger variety of products. We further break down the definition of product line depth by container size, package size and container type (can or bottle). Specifically, we have four types of product variety of a brand: "*container size variety by can*", "*container size variety by bottle*", "*package size variety by* *can*", and "*package size variety by bottle*". We also include $Variety_{jt}^2$ into the utility function. By including the square term of the product variety variable, we expect to determine whether market demand is concave or convex in product variety (Draganska and Jain, 2005). Or in other words, whether there is an increasing or decreasing rate of return for larger product variety.

ξ_j captures the unobserved product characteristics of beer product *j*. ϵ_{ijdt} is a mean zero stochastic error term that follows an i.i.d. Type I extreme value distribution, with a density $f(\varepsilon)$. In addition, there might be unobservable factors changing over the time and location which might affect consumer's decision. Thus, we also include time and DMA fixed effects. Lastly, we include brand and type fixed effect to control for firm specific consumers' preferences. We have 19 different types of beer products and 50 different brands in our sample.

The consumer will choose the beer product which gives him the highest utility. Assuming i.i.d. Type I extreme value distribution for the error terms, the market share of product *j* in market *d* at time *t* is given by

$$s_{jdt} = \frac{exp\left(\alpha_0+\alpha_1 X_j+\alpha_2 p_{jdt}+\alpha_3 Variety_{jt}+\alpha_4 Variety_{jt}^2+\xi_j\right)}{1+\sum_{k=1}^{J} exp(\alpha_0+\alpha_1 X_k+\alpha_2 p_{kdt}+\alpha_3 Variety_{kt}+\alpha_4 Variety_{kt}^2+\xi_j)} \tag{2}$$

To complete the model, the option of a product selection outside the choice set is also given to the consumers. The utility of the outside option is normalized to be constant over time and equal to zero. Therefore, the market share of the outside option is given by

$$s_0 = \frac{1}{1+\sum_{k=1}^{J} \exp(\alpha_0+\alpha_1 X_k+\alpha_2 p_{kdt}+\alpha_3 Variety_{kt}+\alpha_4 Variety_{kt}^2+\xi_j)} \tag{3}$$

Taking the ratio of the market share of the product *j* with respect to s_0;

$$\frac{s_{jdt}}{s_0} = \exp\left(\alpha_0 + \alpha_1 X_j + \alpha_2 p_{jdt} + \alpha_3 Variety_{jt} + \alpha_4 Variety_{jt}^2 + \xi_j\right) \tag{4}$$

Taking log of both sides, our model yields the econometric specification of the demand side as follows:

$$\ln\left(s_{jdt}\right) - \ln(s_0) = \alpha_0 + \alpha_1 X_j + \alpha_2 p_{jdt} + \alpha_3 Variety_{jt} + \alpha_4 Variety_{jt}^2 + \xi_j \tag{5}$$

Supply Side

Firms compete in prices and product variety assuming a Bertrand-Nash equilibrium. They maximize their profits by choosing the optimal number of product varieties to offer and then setting one price for each product they carry.

Let J_m be the set of beer products produced by firm *m*, which is a subset of all products available, *J*. Then firm *m*'s problem is to maximize its profits at time *t* by determine how many products to offer and the optimal prices for all products:

$$\pi_{mdt} = \sum_{j \in J_m}\left(p_{jdt}^m - c_{jdt}^m\right) s_{jdt}^m M - g\left(Variety_{jt}\right) \tag{6}$$

where p_{jdt}^m is the price of the beer product *j* in market *d* and s_{jdt}^m is the market share of beer product *j* at time *t*. *M* denotes the potential market size in each DMA (market *d*). This market size is defined by multiplying the per capita alcohol (beer, sprit and wine) consumption by total population in the considered market. c_{jdt}^m is the corresponding marginal cost for production. In particular, the marginal costs can be expressed as:

$$c_{jdt}^m = \omega_{jdt}' \gamma_j + \eta_{jdt} \tag{7}$$

where ω'_{jdt} is a vector of cost shifters, which consists of wages, factor prices, etc. and η_{jdt} is a random supply shock, which is assumed to be independent of ϵ_{ijdt}. $g(Variety_{jt})$ is the fixed costs of product variety for the firm. Specifically, we specify $g(Variety_{jt})$ as a quadratic function of product variety, which allows the relationship to be either linear, concave or convex depending on the signs of the estimated coefficients. Since only derivatives will be used in the estimation, we specify the marginal cost of product variety as:

$$g'(Variety_{jt}) = \beta_1 + \beta_2 Variety_{jt} + w_{jt} \tag{8}$$

where w_{jt} is error term, which captures the random fluctuations in the marginal costs of product variety. w_{jt} is assumed to be independent of ϵ_{ijdt}, but is allowed to be correlated with the unobserved product characteristics ξ_j and the supply shock η_{jdt}.

Assuming a Nash-Bertrand equilibrium in prices, the first order conditions for the profit function with respect to the prices given by

$$\frac{\partial \pi_{mdt}}{\partial p_{jdt}^m} = M s_{jdt}^m + M \sum_{k=1}^{J} (p_{kdt}^m - c_{kdt}^m) * \Omega_{jk} \frac{\partial s_{kdt}^m}{\partial p_{jdt}^m} = 0 \tag{9}$$

$$\frac{\partial \pi_{mdt}}{\partial Variety_{jt}} = M \sum_{k=1}^{J} (p_{kdt}^m - c_{kdt}^m) * \Omega_{jk} \frac{\partial s_{kdt}^m}{\partial Variety_{jt}} - g'(Variety_{jt}) = 0 \tag{10}$$

where Ω_{jk} is an ownership matrix to account for ownership patterns, which is equal to 1, if both products j and k are owned by the same firm and is equal to 0 otherwise. Further,

$$\frac{\partial s_{kdt}^m}{\partial p_{jdt}^m} = \begin{cases} -\alpha_2 s_{jdt}(1 - s_{jdt}) & if\ j = k \\ \alpha_2 s_{jdt} \mathrm{s_{kdt}} & if\ j \neq k \end{cases} \tag{11}$$

$$\frac{\partial s_{kdt}^{m}}{\partial Variety_{jt}} = \begin{cases} (\alpha_3 + 2\alpha_4 Variety_{jt}) s_{jdt}(1 - s_{jdt}) & if\ j = k \\ -(\alpha_3 + 2\alpha_4 Variety_{jt}) s_{jdt} \mathrm{s}_{\mathrm{kdt}} & if\ j \neq k \end{cases} \tag{12}$$

The first order conditions can then be expressed in the following matrix format as;

$$PCM = (p - c) = (-\Omega * \Delta s)^{-1} s \tag{13}$$

$$-M\left(\Omega * \Delta Variety_{jt}\right)(\Omega * \Delta s)^{-1} s = g' \tag{14}$$

where Δs and $\Delta Variety_{jt}$ are the matrices of derivatives whose *(j, k)* element is given by $\frac{\partial s_{kdt}^{m}}{\partial p_{jdt}^{m}}$ and $\frac{\partial s_{kdt}^{m}}{\partial Variety_{jt}}$respectively.

Estimation

By combing the demand side equation (5) and the marginal cost function (7) with the F.O.Cs of the firm with respect to price and product variety in equation (13) and (14), we have a system of 3J equations to be estimated simultaneously:

$$\ln\left(s_{jdt}\right) - \ln(s_0) - \ \alpha_1 x_{jt} + \alpha_2 p_{jdt} - \ \alpha_3 Variety_{jt} - \alpha_4 Variety_{jt}^2 = \xi_{jt} \tag{15}$$

$$\left(\frac{1}{\alpha_2}\right)(\alpha_3 + 2\ \alpha_4 pv_{bt}) M s_{jdt} - \beta_1 - \beta_2 Variety_{jt} = \ w_{jt} \tag{16}$$

$$p_{jdt} - \omega_{jdt}' \gamma_j - \left(\frac{1}{\alpha_2}\right)\left(\frac{1}{1 - \sum_{k \neq j} s_{kt}}\right) = \eta_{jdt} \tag{17}$$

We use 2SLS to estimate the parameters of the model and estimate these three equations simultaneously. As seen clearly in equations (15)-(17), prices, market shares and product variety are determined in the equilibrium simultaneously and correlated with the error terms: $\xi_{jt}, w_{jt}, \eta_{jdt}$. This brings out the endogeneity problem of these variables.

The instrumental variables used in the estimation process should be correlated with the endogenous variables but uncorrelated with the error term. Therefore, we use prices of the same products in different markets (Hausman et al. 1994), electric prices, wheat prices, natural gas prices, oil price, grain prices, average industry wages, energy prices, and producer price index in beer industry. These instruments, other than prices in other markets, are cost shifters and are not correlated with the market specific demand shocks. Prices of the same products in other markets are also commonly used in discrete choice model literature. The same product's prices are likely to be correlated across different markets. However, they should not be correlated with specific demand shocks of other markets.

3.4 Empirical Results

Results from Demand and Supply Sides Estimation

The results from the demand estimation are presented in Table 3. We first estimate the model using different definitions of product variety, package and size, separately. Column 1 shows the estimated coefficient using only package size variety. All coefficients have expected signs. The coefficient of price is negative and statistically significant. Consumers prefer beer products with higher alcohol content but lower calories. This is consistent with a recent increase in consumption of light beers, as obesity has been a leading health crisis for Americans for decades. Domestic beer, however, has a negative and significant coefficient, suggesting that imported products are more popular in the beer market. Consumers buy premium priced imported beers, even though they are more expensive.

The second panel presents the estimated coefficients of product line depth, which are of special interests. The estimated coefficients of *Package size variety by can* and *Package size variety by bottle* are all positive and significant, implying that consumers prefer brands that offer a larger product variety for both canned and bottled beers. Further, the square terms of both varieties are negative and significant. This suggests that increasing product depth via package size variety brings higher market shares for beer brands but at a diminishing rate. The estimated coefficient of *Package size variety by bottle* is 5.84, which is significantly higher than that of *Package size variety by can*, 1.33. This implies that consumers prefer more packaging options for bottled beers.

In Column 2 of Table 3, we present the estimation results using container size variety to define product line depth. Overall, the estimated coefficients for product characteristics and prices are significant with expected signs, telling a similar story. In terms of product variety, the main and squared termcoefficients of *Container Size variety by bottle* are positive and significant, suggesting that consumers also like brands that offers more container size options for bottled beer, but at a diminishing rate. The main coefficient for *Container Size variety by can* is not significant whereas the squared term is. This suggests a less conclusive effect for cans.

To see a combined effect of package size and container size varieties, we further estimate the model with both measures included. Results are shown in Column 3 of Table 3. Increasing container size variety with bottles or cans has a positive and significant impact on consumer choices, but at a diminishing rate. On the contrary, there is a negative effect of package size variety variables while their square terms have a positive effect on market demand. These results provide important implications for beer firms. In particualr, an increase in container size variety has increasing benefits that diminishes at some level. Alternatively, these results suggest that beer brands must produce a certain amount of package size variety so that they will not lose their market share. That is, with only a limited amount of package variety, brands have lower market share. After some threshold, however, they increasing package size variety results in higher market shares.

These results identify important implications for how a beer producer might manage their product line depth strategy. In this particular case, a beer producer might benefit from a product line depth strategy of higher package size variety and lower container size variety to gain their highest market share. At the same time, our results do not identify the limit at which increasing package size variety no longer pays off. Attempting to estimate models with a cubic term failed to converge. As Iyengar and Lepper (2000) explained, the choice sets with more options are more likely to be chosen. However, after a point, mental cost of considering more options also increases, which lowers the likelihood of choosing the set. Thus, the best strategy for firms to provide the optimal number of products. Our results provide important insights for beer firms in terms of choosing optimal number and form of product line depth.

The mean own price elasticity across all DMA's is estimated to be -5.8, indicating an elastic demand for the beer industry. Although there are studies finding an inelastic demand for beer industry, all of these studies are in the aggregate level. Given that our estimation strategy is the product-level, the estimated mean elasticity is in line with other studies in the literature using a similar approach. For example, Hausman et. al (1994) calculates segment level elasticities and finds elastic demand for beer industry. The elasticities calculated change between -3.76 (for Genesee Light) and -6.2 (for Milwaukee’s Best).

3.5 Estimated Markups and Simulation

We calculate the brand markup using equation (13) and the estimated coefficients for each brand (Table 4). Importantly, each brand is grouped according to the parent company that markets the brand. For the majority of our brands, the same company that brews the beer also markets the beer. However, our data also includes several firms which import beer into the US, but do not brew the beer or have acquired numerous breweries and manage their brewing production and marketing.We identify these firms in Table 4. For each firm, we average the markups by firm, brand, time, and DMA.

Estimated markups tell us the same story about the industry structure as we explain previously. Firms increase their product line depth to capture more consumer surplus and gain higher profits. The mass producers, Anheuser Bush and Miller, have the highest number of product line depth in general and also the highest markups. Following the two industry leaders, the international brewers, Crown Imports and Heineken also enjoy higher markups. In particular, Corona Extra from Crown Imports is the number one imported beer in the USA and the number six beer overall in terms of sales.[22] Merchant Du Vin has similar markups to Craft Brewers, which are lower than the mass producers. This may be explained by the type of beer that Merchant Du Vin imports, which tend to be smaller in production size and offer more specialized styles of beer. Similarly, craft brewers have lower levels of production and more unique styles of beer. Further, as shown in Table 2, they generally have significantly lower numbers of package size variety and container size variety, compare to imported brewers and mass producers. Overall, in the beer industry, the higher the product line depth, the higher the estimated markups for the brand.

[22] See http://www.crownimportsllc.com/aboutus/aboutus.htm

Simulations

Previous results confirm the positive effect of product line depth on consumer demand, market shares, and firms' markups. In this section, using the estimate coefficients, we conduct a series of counterfactual simulations to examine how consumers' consumption of beer products and market shares might be affected by alternative product line depth choices. Table 5 illustrates the simulation results. Column 1 and 2 presents the average percentage changes in mean predicted market shares in a DMA as we increase container size variety by can and bottle, respectively. Column 3 and 4 depict how the predicted market shares would change if we increase package size variety by bottle and can, respectively.

Simulation results provide interesting findings. As we increase container size variety by can by one unit, the average predicted market shares increases but start to diminish after the third unit of increase. For bottled beers, the mean market share reaches the highest increase when the number of container size variety is increased by 3 units.

According to our estimation results, package size variety must meet some minimal threshold before having an effect on market share. As expected, an increase in package size variety by can starts to have a positive effect on market share after a 4 unit increase. Similarly, an increase in package size variety by bottle starts to increase market share after a 4 unit increase. An interesting result to our simulation is that the effect diminishes after the 5th unit.

All together, these findings suggest that firms can increase market share by identifying the optimal number of varieties to provide on retail shelf space. Intuitively, it seems that by extending product depth, firms are able to win shelf space without necessarily incurring significant additional costs.

3.6 Conclusion

The impact of product line length on the supply and demand in different industries has been discussed extensively in the literature. However, to our knowledge, little work has been done regarding the impact of product line depth on consumer choices and firm performance. Our results provide important insights regarding shelf space competition in the beer industry. In particular, in our data set the optimal product line depth decision for brewers is to extend the product line depth by providing more package size and container options with relatively more of the former. By offering a larger variety of packages, which are more easily stocked, it is possible for brewers to obtain more valuable shelf-space in grocery stores. Further, by having a variety of package sizes in stores, brewers can create a type of billboard effect where their brand name is widely advertised across more space and thus may ultimately create barriers for new entrants into the market.

Our analysis highlights the potential benefits of increasing product depth. Using another data set or time period, however, we might alternatively find that firms are providing an excessive number of package or container options. Consequently, decreasing their product line results in greater profits. In such a case, excessive product line extension may ultimately lead to no increase in market share, or cannibalization of market share, while still incurring additional costs.

Another consideration of our analysis is the definition of the markets we are analyzing. Our data set primarily includes grocery stores and supermarkets, but excluded liquor and package stores. The implications of stocking grocery stores may be different than liquor stores for several reasons. First, beer sold in grocery stores competes for shelf space with not only beer products, but other food products. To that point, even the clientele at grocery stores have a different agenda (buying food and household items) than clientele at a liquor store (buying alcohol). Second, liquor stores often offer a greater variety of beer selection than grocery stores. Anecdotally, liquor stores are more often able and willing to carry more unique or specialized beer products. This alludes to our final point, which is that our analysis is clearly affected by the types of products we are studying. Grocery stores sell large quantities of mass produced beer. Our results may vary if we focused on liquor stores that do not necessarily emphasize mass produced beer. To that point, the pricing of products is likely to vary as well.

References

Bayus, B. and W. Putsis.1999. "Product Proliferation: An Empirical Analysis of Product Line Determinants and Market Outcomes," *Marketing Science*, 18, 137–153.

Beer Institute. 2002-2003. "Annual Report".

Brant Ilan, Byron Ellen, and Zimmerman Ann. 2009. The Wall Street Journal. Online access: http://online.wsj.com/news/articles/SB124597382334357329

Chong, J.-K., Ho T-H, and Tang S. C. 1998. "Product Structure, Brand Width and Brand Share," *Product Variety Management*: Research Advances, Boston: Kluwer Academic, pp. 39–64.

Corey M. Reardon (2004), "A New Definition," Label Feature Report, Primedia Business Magazines & Media, Inc.

Draganska M. and Jain C. D. 2005. "Product-Line Length As A Competitive Tool," *Journal of Economics and Management Strategy*, 14:1-28.

Jerry Hausman, Gregory Leonard and J. Douglas Zona. 1994. "Competitive Analysis with Differentiated Products". *Annales d'Economie et de Statistique* – N34.

Kadiyali, V., N. Vilcassim, and P. Chintagunta. 1999. "Product Line Extensions and Competitive Market Interactions: An Empirical Analysis," *Journal of Econometrics*, 89, 339–363.

Kekre, S., K. Srinivasan. 1990. "Broader product line: a necessity to achieve success?" *Management Sci*. October 1216–1231.

Lancaster, K. 1990. "The economics of product variety: a survey," *Marketing Sci*., 9 (Summer) 189–206.

Moorthy, K.1984. "Market Segmentation, Self-Selection, and Product Line Design," *Marketing Science*, 3(4), 288–307.

Printers' Ink. 1963. "What is Missing in Beer Marketing?" November 29: 25-41.

Putsis, W.1997. "An Empirical Study of the Effect of Brand Proliferation on Private Label—National Brand Pricing Behavior," *Review of Industrial Organization*, 12, 355–371.

S. and M. Lepper. 2000. "When Choice is Demotivating: Can One Desire Too Much of a Good Thing,?" *Journal of Personality and Social Psychology*, 76, 995–1006.

Tremblay J. V. and Tremblay H. C. 2005. "The U.S. Brewing Industry: Data and Economic Analysis," Cambridge, MA: MIT Press.

Table 1: Monthly DMA-Level Summary Statistics

Variable	Full Sample		Subsample			
			Can		Bottle	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Market Share (%)	0.43	0.83	0.53	0.85	0.41	0.89
Price ($/ounce)	0.09	0.05	0.06	0.02	0.10	0.05
Alcohol Content (per ounce)	0.42	0.07	0.44	0.08	0.41	0.04
Calories (per ounce)	12.51	1.73	12.27	1.80	12.68	1.67
Domestic Beer	0.64	0.48	0.89	0.31	0.49	0.50
Brand Product Variety						
Package variety by can	3.23	2.78				
Package variety by bottle	3.88	2.29				
Size variety by can	1.77	1.39				
Size variety by bottle	2.39	1.89				
No. of Observations	48,279		19,181		28,409	

Note: DMAs included are Atlanta, Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York, San Francisco and Seattle.

The frequency of observations is progressing four weeks blocks from 2008 to 2012.

Table 2: Monthly DMA-Level Summary Statistics by Firm Types

Variable	Mass Producers		International Brewers		Craft Brewers	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Market Share (%)	0.43	0.73	0.74	1.41	0.22	0.33
Price ($/ounce)	0.07	0.02	0.11	0.02	0.12	0.08
Alcohol Content (per ounce)	0.43	0.07	0.40	0.03	0.41	0.06
Calories (per ounce)	12.35	1.83	12.45	0.85	13.16	1.88
Domestic Beer	0.78	0.42	0.00	0.00	0.86	0.35
Product Variety						
Package Size variety by can	4.26	2.68	2.36	1.97	0.60	1.55
Package Size variety by bottle	4.28	2.66	3.81	1.07	2.56	0.96
Container size variety by can	2.25	1.24	1.49	1.23	0.38	0.91
Container size variety by bottle	2.79	2.22	1.92	0.83	1.49	0.61
No. of Observations	30,242		9,296		8,741	

Note: Mass producers are Anheuser Bush and Miller Coors. International brewers are Crown Imports and Heineken. Craft brewers are Alaskan Brewing, Boston Beer Company, C Dean Metropoulos, Craft Brewers Alliance, Deschutes Brewery, Diageo Plc, Full Sail Brewing, Merchant Du Vin Corp., New Belgium Brewing, North American Breweries, and Sierra Nevada Breweing. DMAs included are Atlanta, Boston, Chicago, Dallas, Detroit, Los Angeles, Miami, New York, San Francisco and Seattle. The frequency of observations is progressing four weeks blocks from 2008 to 2012.

Table 3: Estimation Results

Variables	(1)	(2)	(3)
Price ($/ounce)	-16.377***	-21.131***	-66.748***
	(2.937)	(5.301)	(15.69)
Alcohol Content (per ounce)	16.463***	16.138***	12.185*
	(1.542)	(3.049)	(6.33)
Calories (per ounce)	-0.051***	-0.057*	-0.073
	(0.017)	(0.032)	(0.07)
Domestic Beer	-13.048***	-13.200***	-22.775***
	(1.254)	(1.356)	(7.46)
Product Line Depth			
Package size variety by can	1.328**		-18.647***
	(0.519)		(6.35)
Package size variety by can square	-0.119*		1.911***
	(0.068)		(0.61)
Package size variety by bottle	5.840***		-10.205***
	(0.354)		(2.66)
Package size variety by bottle square	-0.291***		0.422**
	(0.029)		(0.18)
Container size variety by can		3.282	31.885***
		(2.061)	(9.63)
Container size variety by can square		-0.965*	-6.345***
		(0.552)	(1.90)
Container size variety by bottle		15.786***	33.540***

		(1.185)	(5.06)
Container size variety by bottle square		-1.540***	-2.712***
		(0.173)	(0.51)
Months FE	Yes	Yes	Yes
DMA FE	Yes	Yes	Yes
Brand FE	Yes	Yes	Yes
Beer Type FE	Yes	Yes	Yes
F-test for price	31.1	15.89	18.1
F-test for package variety by can	6.56		8.62
F-test for package variety by bottle	272.36		14.78
F-test for size variety by can		2.54	10.97
F-test for size variety by bottle		177.46	44.02
Observations	48,279	48,279	48,279

Note: The frequency of observation is 13 four-week blocks annually from 2008 to 2012 from 12 DMAs. The first 100 products having the largest market share in a DMA were chosen and the same products were appended from different DMAs. If any product is not available in any markets, it is excluded from the sample. Standard errors are in parentheses. *** denotes statistical significance at 1% level, and while ** denotes statistical level at 5%, * denotes statistical level at 10%.

Table 4: Estimated Markups by Firms

Firm Name	Average Markup
Mass Producers	
ANHEUSER BUSCH	1.2323
MILLER COORS	1.2305
International Brewers	
CROWN IMPORTS[a]	1.2141
HEINEKEN	1.2098
MERCHANT DU VIN[a]	1.2049
Craft Brewers	
ALASKAN BREW	1.2072
BOSTON BEER	1.2062
DESCHUTES BRE.	1.2061
NEW BELGIUM	1.2056
FULL SAIL BRE.	1.2055
SIERRA NEVADA	1.2052
CRAFT BREWERS[b]	1.2073
Miscellaneous[c]	
C DEAN METROPOULOS	1.2124
NORTH AMERICAN BREWERIES	1.2065
DIAGEO PLC	1.2051

a. These companies import beer into the US and are not directly involved with brewing beer.

b. Some parent companies of the craft brewers are not identified in our data.

c. These companies have acquired multiple breweries and manage their production and marketing

Table 5: Percentage Increase in Mean Predicted Market Shares Across All DMAs After a Unit Increase in Variety Variables

	(1)	(2)	(3)	(4)
Increase in Variety	Container Size Variety by Can	Container Size Variety by Bottle	Package Size Variety by Can	Package Size Variety by Bottle
variety + 1	21.39	-37.85	-0.09	-0.48
variety + 2	0.95	-42.71	-2.03	-25.65
variety + 3	-98.66	10.38	-9.71	-19.01
variety + 4	0	-3.70	5.20	46.66
variety + 5	0	0	0	13.54
variety + 6	0	0	0	-4.19
variety + 7	0	0	0	-13.70
variety + 8	0	0	0	0

Note: Column 1 shows percentage increase in predicted market shares, if we increase the size variety by can consecutively. Column 2 shows percentage increase in predicted market shares, if we increase the size variety by bottle consecutively. Column 3 shows percentage increase in predicted market shares, if we increase the package variety by can consecutively. Lastly, column 4 shows percentage increase in predicted market shares following a unit increase in package variety by bottle. Mean predicted market shares across all DMAs are calculated by averaging brand level predicted market shares across all markets. Brand level predicted market shares, on the other hand, are calculated by aggregating product level market shares by brand by market. Values show percentage change in predicted market shares between two consecutive increases.